Large-scale automated emission measurement of individual vehicles with point sampling

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Abstract. Currently, emissions from internal combustion vehicles are not properly monitored throughout their life cycle. In particular, a small share of vehicles (< 20 %) ~~of poorly maintained or tampered vehicles~~ with malfunctioning after-treatment systems and old vehicles with outdated engine technology are responsible for the majority (60-90 %) of traffic-related emissions. Remote emission sensing (RES) is a method used for screening emissions from a large number of in-use vehicles.

5 Commercial open-path RES systems are capable of providing emission factors for many gaseous compounds, but they are less accurate and reliable for particulate matter (PM). Point sampling (PS) is an extractive RES method where a portion of the exhaust is sampled and then analyzed. So far, PS studies have been conducted predominantly on a rather small scale and have mainly analyzed heavy duty vehicles (HDV), which have high exhaust flow rates. In this work, we present a comprehensive PS system that can be used for large-scale screening of PM and gas emissions, largely independent of the vehicle type. The

10 developed data analysis framework is capable of processing data from ~~1,000s~~ thousands of vehicles. The core of the data analysis is our peak detection algorithm (TUG-PDA), which determines and separates emissions down to a spacing of just a few seconds between vehicles. We present a detailed evaluation of the main influencing factors on PS measurements by using about 100,000 vehicle records collected from several measurement locations, mainly in urban areas. We show the capability of the emission screening by providing real-world black carbon (BC), particle number (PN) and ~~NO_x~~ nitrogen oxides (NO_x) emission

15 trends for various vehicle categories such as diesel and petrol passenger cars or HDVs. Comparisons with open-path RES and PS studies show overall good agreement and demonstrate the applicability even for the latest Euro emission standards, where current open-path RES systems reach their limits.

1 Introduction

Exhaust emissions from combustion-based vehicles are negatively affecting human health and our environment. Of specific in-

20 terest are NO_x and particulate matter (PM) emissions due to the known impact on health, environment and climate (Mannucci et al., 2015; EEA, 2017). ~~NO_x~~ Nitrogen oxide (NO_x) emissions remain a widespread problem, especially for diesel-powered vehicles, where tampered ~~and defective vehicles contribute to~~, defective and old vehicles are the main source of high emission

levels (Meyer et al., 2023). For PM it is well known from literature, that a small share of vehicles (< 20 %) contribute to the vast amount ~~of emissions~~ (60-90 %) ~~due to malfunction~~ of emissions (Park et al., 2011; Burtscher et al., 2019; Boveroux et al., 2019; Bainschab ~~.~~ This is due to malfunctioning after-treatment systems, such as defective diesel particulate ~~filter~~ filters (DPF) ~~(Park et al., 2011; Burtscher et~~ and old vehicles with degenerated or outdated technologies. It would be highly beneficial to human health and our environment if these high emitters could be identified and subsequently maintained ~~in order~~ to significantly reduce emissions. Most ~~of~~ current regulations are only related to type approval procedures, but do not consider deterioration (e.g., of the exhaust after-treatment system), defects ~~which~~ that are not properly repaired or tampering that occurs in the lifetime of the vehicles (Mock and German, 2015; Bainschab et al., 2020). Particle number (PN) ~~concentrations~~ and black carbon (BC) are two PM metrics of particular interest. In addition to its impact on health and climate, BC is a suitable tracer for vehicles with high PM emissions (Salimbene et al., 2021; Rönkkö et al., 2023). Interest in real-world PN emissions is growing due to newly introduced regulations (Giechaskiel et al., 2021) and known health effects on the human respiratory and cardiovascular systems (Oberdörster et al., 2005; Brook et al., 2010).

Different strategies exist which try to address these issues. PN concentration measurements during periodic technical inspections ~~(PTI)~~ are currently implemented in several European countries like Germany, the Netherlands, Switzerland and Belgium. The PN inspections should identify malfunctioning vehicles during low-idle operation (Bainschab et al., 2020; Giechaskiel et al., 2020; Melas et al., 2021; Giechaskiel et al., 2021). A disadvantage of ~~PTI~~ the periodic technical inspections is that they are in the best case annual, one-time measurements performed under non real driving conditions, which can potentially be circumvented by tampering or by ~~making wrong measurements.~~ manipulating measurements.

Another approach taken for high emitter identification and the screening of real-world emissions of in-use vehicles is remote emission sensing (RES). RES is employed directly at the roadside to measure emissions from passing vehicles under real driving operating conditions (Bishop et al., 1989; Borken-Kleefeld et al., 2018). One advantage of RES is that the vehicles are measured during their normal operation, which complicates fraud. Commercially available RES systems are open-path systems that detect the light extinction of the exhaust plume at different wavelengths to measure different pollutants emitted by passing vehicles (Bishop et al., 1989; Stedman et al., 1992; Moosmüller et al., 2003; Burgard et al., 2006). These systems deliver statistically acceptable emission factors (~~EF~~EFs) for gaseous species, but EFs are inaccurate for particulates. In particular, PM emissions of the latest Euro emission standards (Euro 6, Euro VI and beyond) are below the quantification limit of open-path RES systems (Gruening et al., 2019; Cha and Sjödin, 2022; Jerksjö et al., 2022). ~~PN emissions~~ Other PM metrics such as PN or BC cannot be accurately determined using these systems~~, which are currently of specific interest (de Jesus et al., 2019; Giechaskiel et al., 2021)~~. Complementary RES concepts exist which can be applied to counteract the downsides of these systems. In plume chasing~~(PC),~~ a measurement vehicle equipped with laboratory grade analyzers traces vehicles under test. Several studies (Ježek et al., 2015; Järvinen et al., 2019; Pöhler et al., 2019; Wang et al., 2020) have shown that reliable EFs can be determined by chasing the vehicle under test over a short time period. The disadvantage of ~~PC~~ plume chasing is that it is a rather labor-intensive method which can only be applied to a small number (< 200) of vehicles per chasing vehicle and day.

Extractive point sampling (PS) is a roadside measurement technique (see Fig. 1) that can be used to capture the plumes from passing vehicles by sampling the diluted exhaust (Hansen and Rosen, 1990; Janhäll and Hallquist, 2005; Hak et al., 2009; Ban-Weiss et al., 2009). Compared to open-path RES systems the installation of the measurement setup is relatively simple. The sample is usually directly extracted at the road surface or at the roadside, as close as possible to the tailpipe of the passing vehicles. A small shelter or a van next to the sample extraction houses the instruments that analyze the captured emissions of the passing vehicles (Hak et al., 2009). PS With PS, particle metrics such as PN and BC as well as gaseous compounds can be measured equally well if suitable instruments are selected. PS studies have predominantly measured heavy duty vehicles (HDV) or buses by sampling from the roadside (Hallquist et al., 2013; Watne et al., 2018; Liu et al., 2019; Zhou et al., 2020) or, by sampling from the top of tunnels or bridges for HDVs with a vertical exhaust pipe, which are common in the US (Ban-Weiss et al., 2008, 2009, 2010; Dallmann et al., 2011, 2012; Preble et al., 2015; Bishop et al., 2015; Preble et al., 2018; Sugrue et al., 2020). In these applications, the plumes can be resolved relatively easily, as specific vehicle types are measured or measurements are carried out at selected locations (e.g. bus stations). In dense traffic, difficulties arise when using instruments with limited dynamic range or large response time because the plumes can not be separated (Hak et al., 2009). Detailed analysis of fleet emissions by characteristics such as emission standard, manufacturer or vehicle age were performed mainly in PS studies measuring HDVs and buses (Dallmann et al., 2011; Bishop et al., 2015; Preble et al., 2015, 2018; Liu et al., 2019; Zhou et al., 2020). PS systems capable of large-scale emission screening independent of vehicle type are rare and have only been applied for vehicles classified by length (Wang et al., 2015, 2017) or number of axes and tires (Ban-Weiss et al., 2008, 2010; Dallmann et al., 2013, 2014) or for gaseous compounds using sensor networks (Chu et al., 2022). To the best of our knowledge, there are only individual PS studies in which the LDV emissions of a few test vehicles were determined based on characteristics such as the Euro emission standard (Hak et al., 2009; Ježek et al., 2015). Analysis of emissions by emission standard, manufacturer or age provides more detailed information, e.g. on whether emission limits are generally being met or whether certain manufactures or vehicles stand out.

In this work, we present a comprehensive PS technique that can be used for large-scale emission screening of individual vehicles, largely independent of the vehicle type. The PS system setup measures different PM metrics as well as gaseous compounds from various vehicle categories such as diesel and petrol passenger cars or HDVs. We show the capability of the system by providing real-world BC, PN and NO$_x$ emission trends. The PS setup can be operated in stand-alone mode and and allows emission measurements to be carried out in dense traffic down to a distance of just a few seconds between the vehicles. The developed core of this work is a data analysis framework that is capable of processing data from 1,000s of vehiclesand includes all processing steps from reading raw time series data up to providing fleet emission statisticsthousands of vehicles. The main part of the data analysis is our peak detection algorithm (TUG-PDA)[1], which separates emissions down to a spacing of a few seconds between the vehicles. We provide a detailed insight into the developed PS methodology by discussing the dependencies and key factors, including instrument selection criteria, measurement site selection, sample extraction, vehicle dependencies and environmental impacts. This work was conducted as part of the H2020 project city air remote emission sensing (CARES) (https://cares-project.eu/)weather influences. We show the capability of the system by

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[1]TUG stands for Technical University of Graz

providing real-world BC, PN and NO_x emission trends for passenger cars and HDVs up to the latest Euro emission standards. We use the term pollutant for all measured analytes except CO_2. Important definitions for RES emission calculations are described in Appendix A.

2 Method

2.1 Measurement setup

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We propose a PS setup as illustrated in Fig. ~~?? to carry out the measurement procedure and the data~~ 1, which allows automated post-processing ~~more autonomously. A picture of the setup taken during one of the measurement campaigns is shown in Fig. ??.~~ down to a small distance between the vehicles. The main components are described below~~:~~.
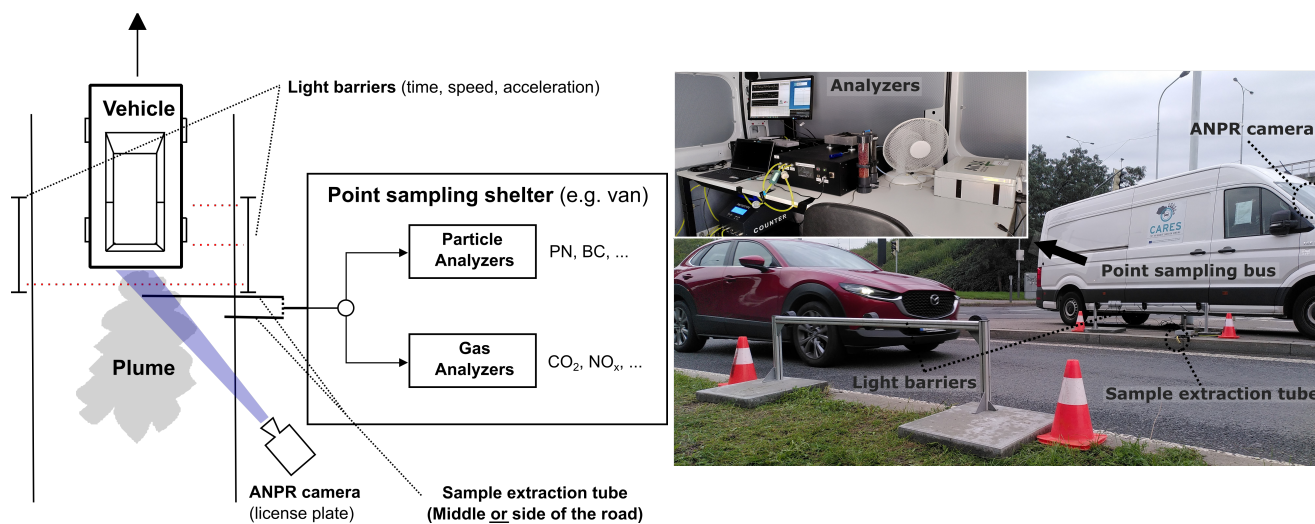

Figure 1. Schematic (**left**) and picture (**right**) of the proposed PS measurement setup, highlighting the required equipment.

Vehicle pass detection: The exact passing time of the vehicles is of great significance for automated post-processing. This is especially the case if several vehicles pass by the measurement location and they have only a small spacing between them. The exact passing time is required during data post-processing to resolve the different plumes correctly. Important variables related to the vehicle condition during the passing are the speed and acceleration. These are required to determine the vehicle specific power (VSP) (see Appendix A3). Emissions from passing vehicles strongly depend on the engine load conditions. Therefore, they must be treated accordingly (Bernard et al., 2018; Davison et al., 2020). For this purpose, we deployed custom-built light barriers ~~in this study~~ to measure the passing time, speed and acceleration of the passing vehicles. Using light barriers restricts the measurement location to single-lane roads or roads with islands between the lanes. Alternatively, vehicle detection can be performed with radar, video, or LiDAR systems.

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License plate recognition: Vehicle technical data are required for several post-processing steps which are described in more detail in the data analysis section later on. Automated number plate recognition (ANPR) systems are commonly used for license plate detection. Depending on the system, additional attributes such as the vehicle pass time or acceleration can be measured. Attention must be paid to the ANPR camera performance, as several influencing factors can exist. License plates are often dirty (especially in winter) or the ANPR camera may not able to correctly detect all the plates of the passing vehicles~~(,~~ especially if they pass within short intervals~~)~~. This impedes data post-processing and underlines the importance of accurate vehicle pass detection. In our setup, the ANPR camera is mounted in the front cabin of the measurement van (see Fig. 1), allowing the license plates to be detected about 2-3 s after the vehicle passes the light barriers. Based on our practical experience, we recommend ~~that~~ determining the vehicle pass time ~~be detected~~ separately from acquiring the license plate data.

~~Schematic Deployed PS setup in one of the measurement campaigns. Schematic (**a**) and picture (**b**) of the proposed PS measurement setup, highlighting the required equipment.~~

Emission measurement: The emission measurement can be split into two main parts: First, the emissions are sampled and second, these are subsequently ~~analyzed~~ analysed with the employed instrumentation. A schematic of the emission measurement setup used during one of the campaigns can be found in Appendix B.

- Sampling: The importance of sample extraction is often underestimated. In PS, the sampling is usually performed with a simple tube which collects the diluted exhaust from the passing vehicles (Hak et al., 2009; Hallquist et al., 2013; Liu et al., 2019; Zhou et al., 2020). ~~The position of the sample inlet can either be in~~ We sample either from the middle of the road ~~by fixing the tube directly on the road or on the side~~ or from the roadside depending on the circumstances (e.g. permissions, road conditions). When sampling from the center of the road, we covered the tube with a small cable duct that was taped to the road. The position of the sampling inlet strongly influences the strength (dilution) of the measured plume and even determines whether the plume can be captured at all. In general, the closer the sample inlet is to the emission source (tailpipe), the smaller the dilution and the higher the capture rate are. We found typical dilution factors between 100 and 500, which is in good agreement with literature (Hak et al., 2009). In addition, the length of the sampling line must be considered in relation to the sample flow. The pressure drop should be minimal and the losses must be taken into account, especially when performing PM measurements (Kulkarni et al., 2011). Attention should also be paid to the material of the tubing. We use tygon tubing for particle measurement because of the flexibility and low particle losses (Giechaskiel et al., 2012).

- Instrumentation: ~~When selecting analyzers for PS applications, attention must be paid to several aspects.~~ Instrument characteristics have a great influence on the quality of the measured emission data. Sugrue et al. (2020) compared high- and low cost BC and CO_2 sensors for their application in PS. They found that low-cost CO_2 sensors may be an adequate substitute for research-grade analyzers in contrast to low-cost BC instruments. In their conclusion, they also emphasized that sensors should be tested under field-conditions. Hak et al. (2009) mentioned in their PS experiments that the small dynamic range of the condensation particle counter ~~(CPC)~~ used constrained the PN measurements. Therefore, they used a dilution volume which extended the measured emission concentration peaks and the fall time of the signals to 5-15

s. The dilution and the relatively large response times of the particle instruments limited the operation to low-traffic situations. Based on the recommendations by Hak et al. (2009) and our own experiences, we have defined the most important requirements for the instruments, which are stated in Table 1. These must be respected to avoid significant problems in PS. In addition, recommendations are given for the different requirements. The emission events associated with the passing vehicles are of very transient nature. To capture these events, instruments must have a fast response time ($t_{90} < 1\text{-}2$ s) and a high time resolution (at least 1 s). In PS, the sampled emissions are highly diluted. Therefore, small concentrations must be resolved. To accurately measure the varying concentrations, the instruments must have a high dynamic range. The measured concentrations can be within a range of four orders of magnitude and depend on the vehicle type, engine state, sampling position and environmental conditions, as well as other factors. It is also important to ensure that the species of interest is measured with minimal cross-sensitivity to other compounds. Therefore, instruments with qualified measurement principles should be selected. Environmental conditions (e.g., temperature, relative humidity, background (BG) concentrations) differ depending on the measurement location, time and season of the year and care should be taken to ensure that they do not affect the instruments. RES campaigns often last for long periods of time (several weeks or months). Therefore, instruments must be stable over the long term. Due to restrictions in the use of calibration sources such as gas bottles or particle sources, the instruments should feature stable calibration over periods of weeks even under harsh environments. Instruments which do not require in-field calibration are preferred. To perform measurements under all conditions, an instrument housing is required, which can be a small shelter or a measurement van.

Problem	Instrument requirement	Recommendation
Transient nature of emission events	Short (t_{90}) response time	$\leq$ 1-2 s
	High time resolution	$\leq$ 1 s
High exhaust dilution in ambient air	Low limit of detection (at 1 s time resolution)	BC: 1 $\mu g\ m^{-3}$ PN: 1,000 # cm^{-3} CO_2: 5 ppm NO_2: 2 ppb NO_x: 5 ppb
Varying concentrations	High dynamic range	BC: 0 - 2 mg m^{-3} PN: 0 - 2e6 # cm^{-3} CO_2: 0 - 3,000 ppm NO_2: 0 - 2,000 ppb NO_x: 0 - 10,000 ppb
Interfering species	Minimal cross sensitivity	Qualified measurement principle
	Minimal artefact formation	For PN: Solid particle number (SPN) measurement

Table 1. Instrument requirements, problem statements and recommendations for PS emission measurements of selected particle metrics and gases.

Monitoring of environmental conditions: It is advantageous to make additional measurements of environmental conditions at the measurement location. Local monitoring of wind speed and direction provides information relevant for the sample extraction and can improve the post-processing. ~~Taking measurements~~ Measurements of precipitation, ambient temperature and relative humidity can also provide ~~meaningful information and can~~ useful information and help to understand ~~abnormalities. We~~ anomalies. We have used data from weather stations either in the area or preferably directly at the PS site. ~~It is advantageous if the weather data is available directly from the measurement location.~~

2.2 Data analysis

The data analysis deals with the determination of representative EFs from the collected measurement data of the captured vehicles. The following aspects must be taken into account:

- Handling and harmonization of data (concentration time series) collected with various instruments.

- Consideration of measurement parameters such as sampling delay or instrument response times.

- Detection and separation of the plumes from the passing vehicles.

- Relation between vehicle pass (time), concentration time series and license plates.

- Dealing with changing environmental conditions (e.g., BG concentrations, other emission sources, weather conditions) that can affect the ~~measurements.~~ measurement

In order to deal with the ~~challenges~~ requirements listed above, a comprehensive ~~data analysis framework was~~ software framework has been developed. The developed procedure ~~has been~~ is divided into three major processing steps, namely the pre-processing, the emission event processing and the emission analysis and statistics. The pre-processing reads the raw time series files from various instruments and the recorded data from the light barriers (time, speed, acceleration) and prepares them for the next processing steps. These data are analysed in the emission event processing part of the procedure. The ~~core of this procedure is our peak detection algorithm (TUG-PDA) which is applied to assign the captured emissions to the passing vehicles. The~~ EFs are then calculated in the emission analysis step, and statistics are performed to subsequently evaluate the EFs. An overview of the data analysis procedure is visualized in Fig. 2. The software framework is designed for modularity and extensibility. New instruments and measurement campaigns can be easily integrated into the framework by copying existing instruments or campaigns and adjusting the parameters. The ~~data analysis~~ software has not been developed for specific instruments and in general any measurement device that provides continuous measurement data can be integrated. However, we strongly recommend to consider the recommendations in Table 1 when selecting instruments to achieve the best possible results. The software framework is implemented in Python by using common libraries such as Pandas, NumPy, Matplotlib, or SciPy. The basic framework of the software can be found here: https://gitlab.com/tug-ems/point-sampling.git.
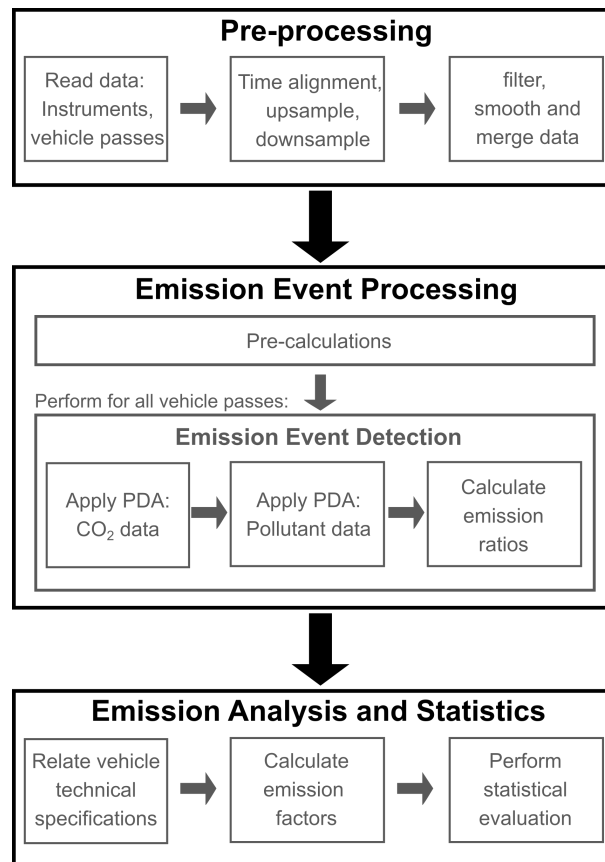
2.2.1 Pre-processing

Figure 2. Overview of the PS data analysis procedure.

In PS campaigns, various Different instruments are often used to measure different exhaust components during PS campaigns (Hallquist et al., 2013; Wang et al., 2015; Ježek et al., 2015; Liu et al., 2019; Sugrue et al., 2020; Zhou et al., 2020). Because various instruments are used, different data formats need to be handled and the time resolution can vary between the devices from instrument to instrument. These heterogeneous datasets are harmonized into one composite dataset in order to appropriately process the data by using one a data analysis procedure. After reading the raw time series from the individual instruments, a time alignment of the data is performed. Different instruments have varying response times which depend on the instrument response function, sample flow and sample tube connection to the instruments. These differences must be compensated for. We manually determine the response times from short manual pollution peaks (e.g., with a lighter) and align the instrument responses based on this event. The response time to the emissions of individual vehicle passes varies depending on the sampling position, exhaust pipe position and environmental conditions. We align the concentration time series data to the vehicle passes which cause the fastest response (e.g., from vehicle with tailpipe on the same side as the sample extraction). Emissions e.g., from vehicles whose tailpipe is on the opposite side of the sampling position are sampled with a delay of a few seconds. In addition, sampling delays between the sample inlet and the instruments must be compensated for. To simplify data

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processing, the time resolution of the CO_2 data is equated to the time resolution of the pollutant data (default time resolution of 0.5 s). ~~Having higher~~ Higher time resolution makes it easier to resolve emission events on smaller time scales. This ~~enables~~
205 allows vehicle passage data to be processed down to a spacing of only a few seconds, as long as the instrument's response time permits. As a final pre-processing step, error-prone data samples (e.g., outliers) are filtered out, the instrument responses are adjusted to each other (by smoothing), and the datasets are merged. If instruments with large differences in response times ($\Delta t > 2$ s) are used, the response function of the instruments must be aligned.

2.2.2 Emission event processing

210 To determine the EFs, the transient emission events associated with the passing vehicles must be properly detected. For that purpose, a dedicated algorithm was developed. The TUG-PDA ~~separately processes the~~ assigns the measured emission concentrations to the by-passing vehicles. The CO_2 time series and the time series of the measured pollutants (e.g., BC, PN, NO_x) are separately processed, since PM and gaseous emissions can occur at a different time. The time series data of CO_2 and pollutants do not have to be perfectly aligned to each other ($\pm$ 1.0 s, see Appendix G) and the response functions of the
215 used instrumentation do not have to be perfectly matched. At the same time, care must be taken to ensure that the CO_2 plume detected ~~of~~ from the passing vehicle is related to the pollutant emission detected. Therefore, ~~checks are implementedwhich compare the duration of the integrated CO_2 and pollutant data and verify if the areas overlap appropriately. The CO_2 data signals are thus processed prior to processing the pollutant emission data using the~~ several quality assurance (QA) measures are implemented. The TUG-PDA ~~. The TUG-PDA~~ relies on the time series data of the measured analyte (e.g., CO_2, BC) ~~,~~
220 and the passing times of the vehicles~~and the defined thresholds for the emission detection as input. If pollutant emissions are processed, the event results from the corresponding CO_2 processing (start and stop time of the integration)are also required.~~. The algorithm is fully configurable with various adjustable parameters defining thresholds or QA measures. Fig. 3 shows the main processing steps of the TUG-PDA algorithm, separated for CO_2 on the left and for pollutant emissions on the right. The TUG-PDA loops through all vehicle pass data and is applied first to CO_2 and afterwards to each pollutant (e.g. NO_x, BC).
225 The CO_2 data signals must be processed first as the results are required for processing the pollutant data. The main processing steps are the same, but several processing steps are only performed when processing CO_2 emissions (plume strength), or when processing pollutant emissions (cross-checks with CO_2). The processing steps are explained in the following paragraphs.

Start conditions: The vehicle pass time is used as the starting point for the plume detection. The TUG-PDA searches around the vehicle pass time (default window: -1 s to 6 s) for a sequence of positive concentration gradients above a defined threshold
230 (see Table 2) of the processed analyte (visualized in Fig. ~~3 shows a flow chart of the~~ 4). The thresholds were determined based on a large number of manual reviews of TUG-PDA ~~with the main processing steps of the algorithm. The TUG-PDA loops through all the vehicle pass data.~~ results. There must be either at least two gradients or one very large gradient (> 10 times the threshold) above the threshold. The time of the first rising gradient is used as the starting point for the plume integration. When processing pollutant emissions, the processing of the current vehicle is skipped if no valid CO_2 plume was detected during
235 CO_2 processing. Several QA measures (shaded boxes in Fig. 3) are implemented to prevent wrongly assigned emissions or inaccurate results. The following tests are performed during the start condition:

- **Vehicle distance:** First, when a new vehicle pass is fetched, it is checked whether the distance ~~(≥ 3 s)~~ to the next vehicle pass is sufficient (> 3 s). If this is not the case, the processing ~~for~~ of the current vehicle is stopped and the algorithm proceeds to the next vehicle. ~~At this small spacing~~ With a spacing of less than 3 s, there is a large uncertainty that emissions will be attributed to the wrong vehicle due to differences in the sampling delay between vehicles. ~~The vehicle pass time is used as a starting point for the plume detection. The TUG-PDA searches from this point onward for a sequence of positive concentration gradients above a defined threshold of the processed analyte (visualized in Fig. 4) . If a sequence of positive gradients has been found, the starting point of the sequence is used as the starting point for the plume integration. Prior to the integration,~~

- **Separability:** The detected gradient (plume) must not be from a previous vehicle. The processing is skipped if either:

  - A rising gradient (start condition) from the previous vehicle is found within a pre-defined time frame (default: 3 s before the vehicle pass of the current vehicle) and the plume directly interferes with the current vehicle.

  - Or a significantly higher pollutant concentration was measured in the last period (default: 25 s) than for the current vehicle and the current vehicle is likely to be affected by this emission. This is the case when the emission of the previous vehicle was much higher than the peak of the current vehicle and the BG concentration before the current vehicle is still significantly higher than the BG without vehicles.

- **Pollutant vs CO_2:** The pollutant peak must start within a pre-defined window compared to the CO_2 peak (default window: -1 to 3 s).

Analyte	Threshold
CO_2	8 ppm s^{-1}
BC	4 (μg m^{-3}) s^{-1}
PN	4,000 (# cm^{-3}) s^{-1}
NO_x	12 ppb s^{-1}

Table 2. Default gradient thresholds defined in the TUG-PDA for the peak search.

BG determination: Before integrating the peak, the BG concentration is determined. We ~~observed~~ divide the BG determination into the following two cases:

- **No interference:** If there is no interference from a previous vehicle, this case is used. We found that the minimum ~~concentration directly~~ of the running mean concentration just before the vehicle pass ~~fits best because~~ was the best fit as it represents the actual condition. ~~Similar approaches were used in~~ In this study we used a window of 4 s (8 samples) before the integration start time. Similar approaches have been used in the literature to determine ~~the BG concentration (Ban-Weiss et al., 2008; Wang et al., 2015). One special case for BG determination is~~ BG concentrations (Ban-Weiss et al., 2008; Wang et al., 2015).
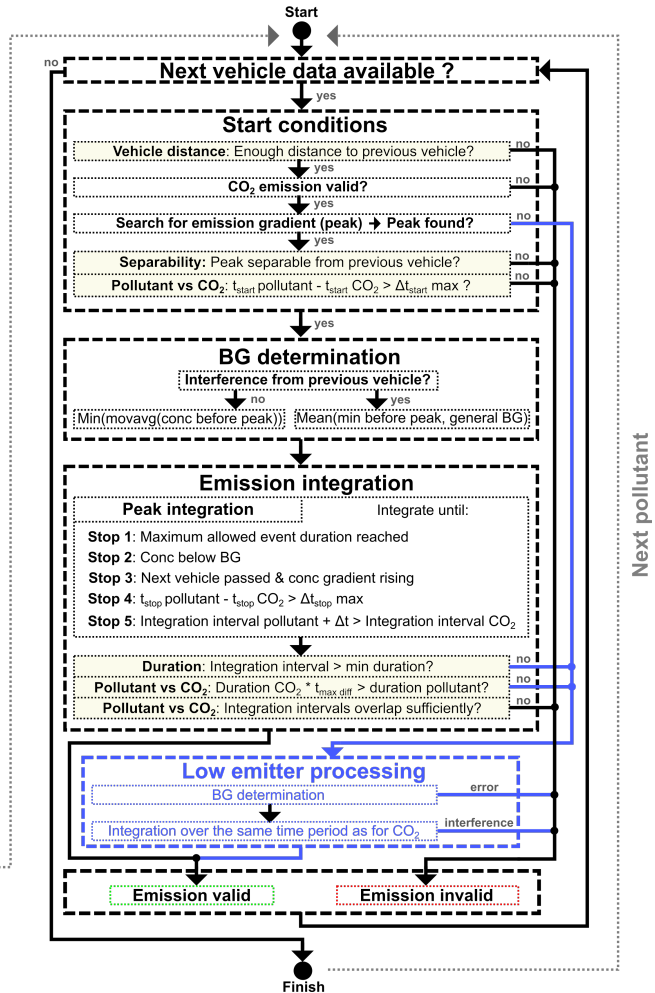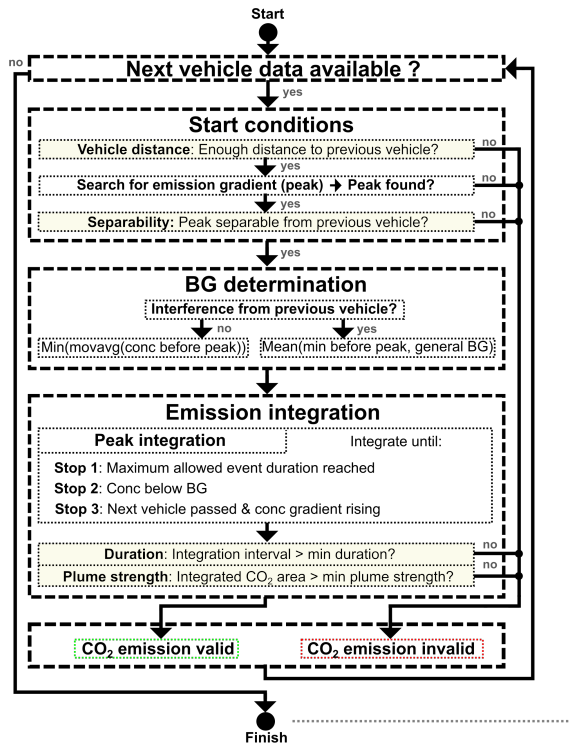
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Figure 3. Emission event processing - flow charts of the peak detection algorithm (TUG-PDA). CO_2 and pollutant (e.g., BC, PN, NO_x) emissions are processed separately. The algorithm is applied first to CO_2 (left) and then to the individual pollutant emissions (right). The shaded boxes are QA conditions. The processing of low emitters is highlighted in blue. The following abbreviations are used: min - minimum, mov avg - moving average, conc - concentration, BG - background.

– Interference: The plumes overlap ~~and the plumes overlap. If this is the case, an interim~~ when vehicles pass the measurement point within a short period of time. In this case, the mean value is taken ~~, i.e. a value between the previously described BG value and a concentration~~ between the median concentration directly before the starting point of the integration (default window size: 3 s) and a general BG value taken within the last ~~minutes which~~ few minutes that is not influenced by vehicles. Here we search for the last time frame in which no vehicle plume was detected. If no such window (default length: 8 s) is found in the last 10 minutes, a statistically determined BG value is calculated by removing emissions above

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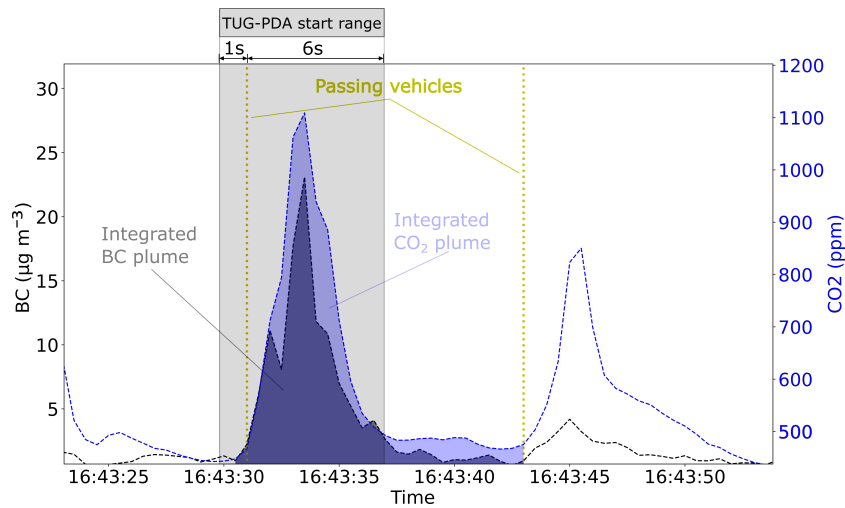
Figure 4. Time series example of sampled PS data (BC, CO$_2$) from two vehicle passages. The integrated areas of the CO$_2$ and BC emission concentrations are highlighted for the first passing vehicle using the TUG-PDA as described in Sect. 2.2.2. The start time range of the algorithm is indicated for the first vehicle pass.

the 75th percentile of the dataset used. A moving average filter (default window size: 30 s) is applied to the resulting dataset and the minimum value is used as BG. Examples of BG subtracted emissions from overlapping plumes are shown in Fig. 5a and 5b.

Emission integration (and separation): After determining the BG, the concentration of the exhaust plume is integrated until one of the defined stop conditions is reached (see Fig. 3):

– A maximum event duration (Stop 1: The maximum allowed duration (default length: 25 s) of the emission event is exceeded.

– Stop 2: The concentration falls below the BG concentration.

– A subsequent vehicle pass occurs, Stop 3: Another vehicle pass is observed and the concentration gradient increases. After integration , several tests are performed to determine whether the captured emission event is valid:

– First, the Stop 4 (Pollutant only): The pollutant integration exceeds the stop time of the CO$_2$ event by a defined value (default: 3 s).

– Stop 5 (Pollutant only): The integration interval of the pollutant emission event (duration of the integrated plume is reviewed to see if it meets a defined minimum value (in this study, three seconds). If this is the case, different areas) exceeds the integration interval of the CO$_2$ emission event by a defined value (default: 1 s).

In addition to the QA measures applied during the start conditions, the following tests are performed for either CO$_2$ or the examined pollutantafter the integration:

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- ~~In case of processing CO$_2$, the integrated area requires a~~ Duration: The integration interval must exceed a minimum value (default: 3 s).

- Plume strength (CO$_2$ only): The integrated CO$_2$ area must be greater than a defined minimum concentration (~~40~~ default: 80 ppm s).

- ~~In the case of examining a pollutant, tests are performed to verify whether the time frames of the integrated areas for the examined pollutant and CO$_2$ coincide. It is not allowed that the duration~~ Pollutant vs CO$_2$: The integration interval of the CO$_2$ emission event including a pre-defined factor (default: $t_{max\_diff} = 0.6$) must not be greater than the integration interval of the pollutant ~~area exceeds the area of CO$_2$~~ emission event.

- Pollutant vs CO$_2$: The CO$_2$ and pollutant integration intervals must overlap to a certain extent (default: by at least 50 percent).

~~If the conditions are met, the~~
The emission event is considered ~~to be valid , and the integrated concentration and the time information (start, stop) for the emission event is stored (~~valid (highlighted in green in Fig. 3) if the conditions are met. The TUG-PDA continues processing the next vehicle pass.

When processing the pollutant data, a special case is implemented in order to consider low emitters (~~vehicles with small pollutant emissions). If a substantial concentration gradient is not found, and the minimum event duration criteria is not fulfilled,~~ Fig. 3, in blue). This is the case if either no emission gradient (peak) was found, the duration of the emission event is below the lower limit of the integration interval, or if the integration interval of CO$_2$ is too long compared to the integration interval of the pollutant. If one of the three conditions is not met, then the pollutant concentration is integrated over the ~~duration of~~ same time period as the captured CO$_2$ event associated with the passing vehicle~~(highlighted in blue in Fig. 3)~~. Similarly to the general procedure, the BG determination is separated into the two cases described (without/with interference) and the integration is stopped if another vehicle pass is observed and the measured concentration increases. After the TUG-PDA has finished ~~the~~ processing, the emission ratios (ER) of each vehicle pass (see Sect. A1) are calculated. ~~The TUG-PDA is fully configurable with various adjustable parameters such as start time range, thresholds, or minimum number of required data samples.~~

~~Emission event detection - Flow chart of the TUG-PDA. CO$_2$ and pollutant (e.g., BC, PN, NO$_x$) emissions are processed individually. Highlighted in green: outcome for pronounced plumes. Highlighted in blue: outcome for low emitters.~~

~~An example of the data processing of the TUG-PDA for CO$_2$ and BC emission concentrations recorded of two passing vehicles is shown in Fig. 4. The passing time is indicated by yellow, vertical, dashed lines. The TUG-PDA algorithm starts searching one second before the vehicle pass for a significant rise in emission concentration. The emission concentrations which are assigned to the first shown vehicle pass are highlighted by the integrated areas of CO$_2$ (shaded in blue) and BC (shaded in black). In this case, the TUG-PDA stopped the integration, because another vehicle pass was identified, and an increasing gradient was found. The plumes from the passing vehicles can be easily separated and an ER can be calculated in this case. The BG concentrations of CO$_2$ and BC are subtracted from the integrated areas. More information on the capabilities and limits of emission separation of densely driving vehicles is provided in Appendix ??.~~

Alternative methodologies exist for emission processing in PS. The captured CO_2 and pollutant emissions are commonly integrated over the same time frame (Ban-Weiss et al., 2009; Ježek et al., 2015; Liu et al., 2019; Zhou et al., 2020). Automated PS emission processing algorithms can also be found in previous studies. Wang et al. (2015) presented a plume identification algorithm that takes different approaches in the case of plume separation (minimum plume length of 10 s) or low emitter detection. Another new approach proposed by Farren et al. (2023) is the so-called rolling regression method. This algorithm simplifies data processing by calculating the ERs for three consecutive data samples, which makes the BG determination redundant. This is a particularly promising approach for short emission events of high emitter. One challenging aspect is of this approach is the determination of low emissions from the latest emission standards. Another aspect is that the instrument responses for CO_2 and measured pollutants must be perfectly matched when taking this approach. The applicability of this approach to evaluate PM pollutants still needs to be studied due to the disparity between gaseous and PM emissions.

2.2.3 Emission analysis and statistics

Once the ERs of passing vehicles have been determined, further analysis requires the vehicle technical data. This is usually obtained from government organizations. It is important to respect the privacy of the license plates captured, which varies from country to country. Several details from the vehicle technical data are required during the emission analysis to calculate EFs and to perform further statistical analysis. The fuel type (e.g., gasoline, diesel) must be known to calculate fuel-based EFs. For the calculation of distance-based EFs, the The CO_2 emissions as measured during the type approval process for type-approval process of the vehicle model are required to calculate the distance-related EFs. In most European countries, the European emission standard class is used to classify vehicles according to their emission limits. Information such as the manufacturer or vehicle category are used to perform detailed evaluations of fleet emissions and to identify unusual emission patterns, such as individual high emitting vehicle models or manufacturers.

As part of our data post-processing procedure, the vehicle technical data as requested from the authorities and detected by the ANPR camera must be related to the ERs. These are then assigned to the passing time as gathered with the light barriers. We use the speed and acceleration information of the passing vehicles to match the passing time with the detected license plate. This generally sounds like a simple task. However, not all license plates are correctly detected by the ANPR camera for various reasons (e.g., dirt, poor light conditions, too little distance between the vehicles). This makes the task of correctly matching the data from the ANPR camera and light barriers challenging, and specially for vehicles that follow each other closely. In our setup, the ANPR camera is mounted in the front cabin of the measurement van (see Fig. ??), allowing the license plates to be detected about 2-3 s after the vehicle passes the light barriers.

3 ~~Results and discussion~~

2.1 Capture rate

In RES, the proportion of valid measurement records is a significant indicator. We call this indicator the capture rate (CR), which is the ratio between the number of vehicle passes for which valid EFs can be calculated and all vehicle passages:

$$CR = \frac{\#\,valid\,EF}{\#\,all\,vehicle\,passes}. \tag{1}$$

355

What is considered as a valid measurement is always subjective. We consider the calculated emissions to be valid if the plume from the passing vehicle was properly captured and an EF can be calculated. This is the case if the following conditions are considered to be true:

- The integrated CO_2 plume is greater than a specified threshold. In this study, ~~40~~ 80 ppm s was used.

360
- The emissions of the passing vehicle can be separated from those of other vehicles. This is not the case if the plumes cannot be separated or if the emissions can't be unambiguously assigned to one vehicle ~~.~~ (see Fig. 3).

3 Results and discussion

3.1 ~~Evaluation of influencing factors~~ TUG-PDA emission separation capabilities

~~In the following part, the most important factors influencing PS measurements are discussed and the resulting impacts are shown~~
365 ~~on basis of around 100, 000 vehicle emission records gathered during 4 measurement campaigns.~~ The ~~measurement campaigns were conducted in the Netherlands, Italy, Poland and Czechia. The results include data from 9 measurement locations. In several figures (e.g., Fig. ??, ??, ??, ??)~~ TUG-PDA tries to resolve emissions down to a small distance (default: 3 s) between the vehicles. Several tests are implemented to determine whether the emissions really come from the current vehicle or are caused by interference from previous vehicles or another source. However, not all cases can be covered and overlapping
370 plumes are difficult to resolve accurately. The plume separation can be tuned using several parameters used in the software. This can be very useful for instruments with different response times and for locations with dense traffic to obtain a sufficient number of measurements. Restricting measuring to low-traffic areas would severely limit the application.

Fig. 5a and Fig. 5b show two PS time series examples that demonstrate the capabilities and the limitations of the TUG-PDA for plume separation from passing vehicles. The BC and CO_2 emissions assigned to the passing vehicles are highlighted in black
375 and blue, respectively. In both examples, the BG concentrations are subtracted from the integrated areas. In the data shown in Fig. 5a, the TUG-PDA is able to separate emissions for three (V1, ~~the results from the different measurement locations are labeled with numbers. Different sampling positions or traffic situations were evaluated on individual locations. These are labeled with x. x (e.g. V3,~~ ~~1.1). This should facilitate the interpretation of the results~~ V4) out of four vehicles. CO_2 and BC peaks are evident for all four passing vehicles, but to varying degrees. For the vehicles V1, V3 the algorithm stops integrating

15

the emissions because another vehicle (V2 and ~~the comparison~~ V4) is passing and the concentrations are rising. For vehicle V4, the integration is stopped because the BG value is undercut. The plume detected from vehicle V2 is invalid because the CO_2 gradient is not above the threshold and the integrated area is below the minimum value (80 ppm s). The algorithm can be easily tuned to detect emissions from vehicle V2, but as plume strength decreases, inaccuracies increase. This is due to the increasing dependence on the BG determination and is even more pronounced when the plumes overlap. Fig. 5b shows a data example where the emissions of most passing vehicles cannot be resolved properly due to high traffic density. The emissions of the vehicles V1 and V2 can be resolved as the distance between the vehicles is large enough (≥ 3 s) and two distinct CO_2 peaks are detected. Both vehicles can be considered as low BC emitters as no BC peaks were measured. No EFs can be determined for the vehicles V4, V5, V8, V9 and V10 because the distance between the vehicles is too small and no distinct CO_2 peaks can be assigned to them. The vehicles V3, V6 and V7 do not show clear CO_2 peaks, either because they are too weak or because they are superimposed by the emissions of a preceding vehicle.

(a) Separable   (b) Not separable
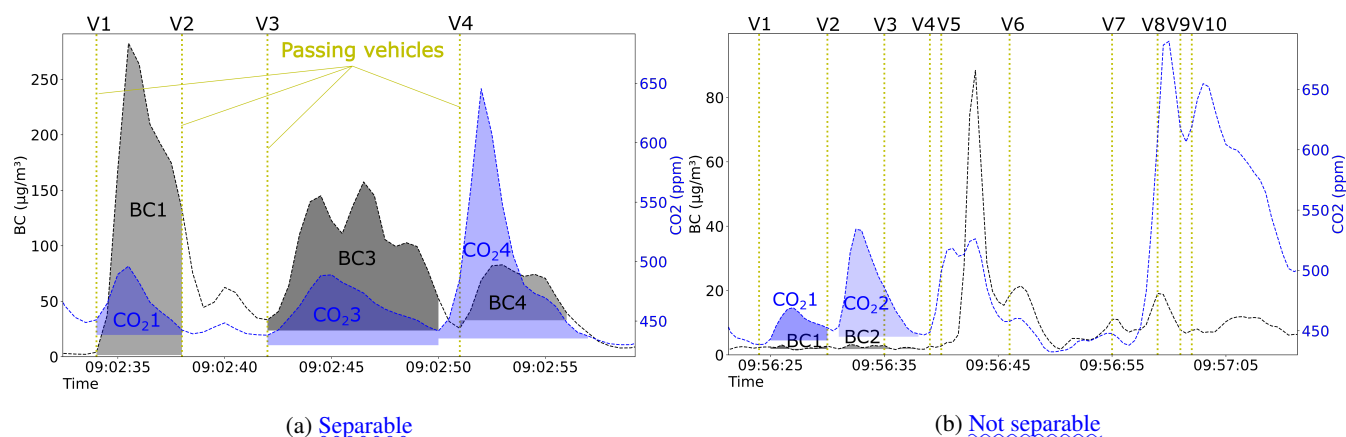
Figure 5. Two PS time series examples (BC, CO_2) from captured plumes. The yellow, vertical, dashed lines mark the point at which the vehicles passed the PS spot. **a)** Emissions can be separated for three (V1, V3, V4) of the four vehicles. The assigned emissions are highlighted in different colors (BC1-BC4 and $CO_2$1-4). **b)** For most vehicle passes, the emissions for individual vehicle passes are not separable. Ten vehicle passes are shown, of which emissions are determined for two (BC1,2 and $CO_2$1,2).

In the current implementation of the TUG-PDA, the BG determination for overlapping plumes is done by calculating an average value between the median concentration directly between the overlapping plumes and a common BG when no vehicle is passing. This is a simple estimation and entails deviations from the actual situation. This can be seen, for example, in Fig. 5a) for vehicle V4. The BC background is overestimated. This results in a too small integrated area (BC4) and thus underestimated emissions. This can also be seen to a smaller extent for vehicle V3, where both CO_2 ($CO_2$3) and BC (BC3) backgrounds are underestimated, leading to an overestimation of both areas.

It is important to know how accurate the determined EFs are due to the assumptions made in the calculations for overlapping plumes and the complexity of resolving superimposed emissions. We therefore assessed the impact of interference from other vehicles/sources on the resulting EFs. The TUG-PDA distinguishes between the following three cases of interference:

400 – Overlap: The plume from the current vehicle overlaps with the plume of a previous vehicle. The two plumes must be separated.

– Cut-off: The plume from the current vehicle interferes with the next vehicle. The emission integration stops for the current vehicle and the entire plume has not been captured.

– Overlap + cut-off: The above two cases are applicable. The plume from the current vehicle is influenced by the plume
405 from the previous vehicle and the exhaust plume from the next vehicle.

These cases are marked in the algorithm and can be used for further analysis. This marking is done individually for the different emission signals (e.g. CO_2, BC, NO_x), as they are processed separately.

As an example, we investigated the influence of interfering plumes on the determined BC emissions of petrol-powered passenger cars. Only overlapping CO_2 signals are taken into account and no superposition of BC emissions. The inclusion
410 of BC interferences distorts the results, as these consist mainly of high emitters (see Appendix Fig. C1). The emission distributions shown (Fig. 6) are separated into a combined data set (with and without interference), measured interference-free emissions, and the three cases in which the TUG-PDA categorizes interference . We did not find a strong influence of plume interference on the results. The determined EFs are statistically comparable between the different ~~impact factors, as they were not determined independently. For the evaluation of the influencing factors , mainly data from the newly developed black~~
415 ~~carbon tracker~~ datasets with and without interference from other vehicles. The largest deviation was found for plumes that were cut-off. The median EFs were 19 % lower than in cases without interference. The sample size shows that the majority of the emissions determined were influenced by an interference. If only plumes without interference were considered, the number of measurements would be greatly reduced.
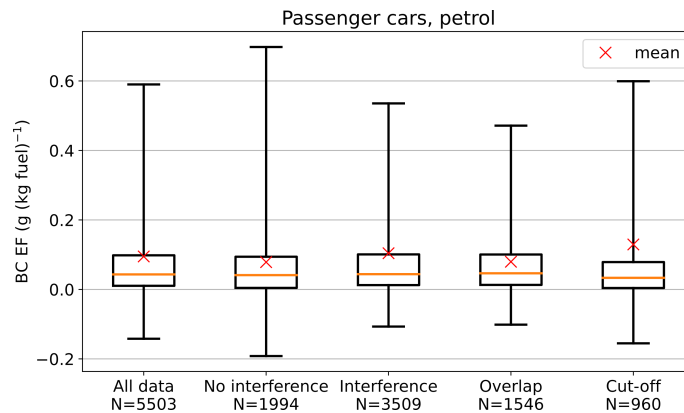

Figure 6. Influence of interference from other vehicles/sources on the BC emission distributions determined with the TUG-PDA. Measured EFs of petrol-powered passenger cars are used for comparison. Interference data includes both overlapping plumes and plume cut-offs (interference = overlap and/or cut-off).

3.2 Factors influencing point sampling measurements

In the following part, the most important factors influencing PS measurements are discussed and the resulting impacts are shown on basis of around 100,000 vehicle emission records gathered during 4 measurement campaigns. The measurement campaigns were conducted in the Netherlands, Italy, Poland and Czechia. The results include data from 9 monitoring sites, with data from the specially developed Black Carbon Tracker (BCT) ~~were used~~ being used to assess the various factors. The BCT measures BC with a photoacoustic based sensor cell and CO_2 with a non-dispersive infrared (NDIR) sensor integrated into one device. The device was developed based on the recommendations listed in Table 1 as part of the CARES project (Knoll et al., 2021). The impact of misaligned measurement data on the resulting ~~EFs~~ ERs is discussed in Appendix G.

3.2.1 ~~Sampling position~~Instrument characteristics

~~The approach used to collect the exhaust has a major impact on quality and strength of the signal. In PS, the sample is commonly extracted either from the side or the middle of the road. The integrated CO_2 concentration of the captured plume of the passing vehicles serves as a marker for comparing sampling positions. Therefore, we compared the CO_2 concentrations when we measured either from the middle, the left, or the right side of the road. If the sample was taken in the middle of the road the sampling tube was fixed directly to the roadway. All three sampling positions were used at least three times during the measurement campaigns.Distributions of mean CO_2 concentrations of the three sampling positions were calculated using the Monte Carlo method by drawing 500 samples of the measured CO_2 concentrations of passing vehicles from each measurement position~~ We compared the characteristics of the custom-designed BCT with those of a commercially available Aethalometer AE33 (Magee Scientific). The Aethalometer AE33 is widely used in environmental science for BC measurements and source appointment and is commonly used in PS studies to quantify BC emissions (Ježek et al., 2015; Preble et al., 2018; Zhou et al., 2020; Sugrue . Laboratory measurements showed a very good correlation ($R^2 = 0.99$) between the Aethalometer and the BCT. Comparable limit of detection (1 ~~,000 times. Sampling from the middle of the road gives on average clearly higher signals as compared to sampling from either side of the road, with a mean and σ of 781 ppm and 1867 ppm, respectively. Sampling from the left (mean: 599 ppm, σ: 914 ppm) delivers on average a higher signal as compared to sampling from the right side (mean: 554 ppm, σ: 995 ppm~~s, 3 σ) were determined for both instruments, with values of 1.01 $\mu g\ m^{-3}$ for the Aethalometer and 1.12 $\mu g\ m^{-3}$ for the BCT. The limit of detection of the instruments defines the extent to which emissions can be resolved. This is particularly important for accurately quantifying emissions from vehicles that meet the latest emission standards. The t_{90} response times of the two instruments were measured in the laboratory: 0.9 s for the BCT and 7 s for the Aethalometer. A small response time enables the separation of highly transient emission events. This determines how close vehicles can drive to each other in order to be able to resolve the emissions. Fig. 7 shows two emission time series of the two instruments during one of the measurement campaigns. Two vehicles pass by the PS spot during the shown time frame with an interval of six seconds. The BCT responds quickly to the captured BC emissions from the first passing vehicle (V1). A ~~Gaussian distribution was assumed and fitted to the three datasets (Fig. E1). In general, the closer the sample is extracted to the exhaust source, the stronger the captured signal is . In most regions in Europe, sampling from the left is favored over the right side. Vehicles from manufacturers in Europe~~

(e.g., VW, BMW, Mercedes, Fiat) have usually the tailpipe on the left-hand side, unlike manufacturers in Asia or the United States (e.g., Toyota, Kia). We also evaluated the mean CR of the CO_2 plumes from the three sampling positions (Fig. ??) . A direct relation is observed between the CO_2 signal strength and the CR. A higher CO_2 signal generally leads to a higher CR. The highest CR can be achieved if the sample extraction is performed from the middle of the road. By using this central setup, a CO_2 plume could be captured for an average of 41.3 distinct peak is noted where the measured concentration is again below 10 % of the vehicles. This relates well to Hak et al. (2009), who reported a CR of about 50 % with their setup sampling from the middle of the road. Sampling from the left delivers on average a CR of 31.6 % as compared to 23.2 % if the sample is extracted from the right side. The variance for measurements in the middle of the road is smaller than at the roadside. At two measurement locations (3 and 7) , the sampling was conducted from both, the roadside and from the center of the road. Two to three times higher CRs were obtained when sampling from the middle of the road (Fig. ?? and Fig. ??). Sampling from the center of the road is less influenced by location and vehicle characteristics such as road width and tail pipe position. The influence of wind conditions is less because the exhaust is sampled in close proximity to the source. In addition to the influence of the sampling side, the sampling height also has a major impact on the sample extraction. Higher CRs and stronger CO_2 signals are achieved at lower sampling inlet heights. This is particularly evident at measurement locations 1 and 2, where the position of the sample inlet was shifted by 3-4 m with slight differences in sampling height (Fig. ??) and road width (Fig. ??) .

peak concentration of the first vehicle when the second vehicle (V2) passed by. The emissions captured for the two vehicles overlap, but they can be separated. In contrast, the Aethalometer response time is much slower and the maximum concentration is reached after the second vehicle (V2) has passed by. The BC emissions from the two vehicles cannot be separated in this case. This is an example that shows how important it is to select instruments with suitable characteristics for PS applications in dense traffic (see Table 1). Individual characteristics that do not meet the requirements of the application can severely affect the measurement data. However, the Aethalometer can also be used for PS, as has already been demonstrated in several studies. The traffic density must be low enough (distance between vehicles greater than 7-10 s) or only certain types of vehicles (e.g. HDVs with vertical exhaust pipes) are measured, which naturally entail a greater distance between exhaust plumes.

Capture rate as a function of the height of the sampling inlet. The numbers represent the different measurement locations. The sampling position (left, middle, right) is highlighted. At measurement sites 1 and 2, sampling was conducted from two positions shifted by 3-4 m on the same side with slight differences in sampling height and road width.

3.2.2 Measurement location and sampling position

Special care must be taken when selecting suitable measurement locations. The selection of the measurement location influences the following aspectsBesides the legal regulations (e.g. for the placement of equipment), the following aspects influence the selection:

– Road properties (single or multi-lane, lane width, road gradient)

– Traffic conditions (traffic flow, distance between passing vehicles, number and type of vehicles)

19
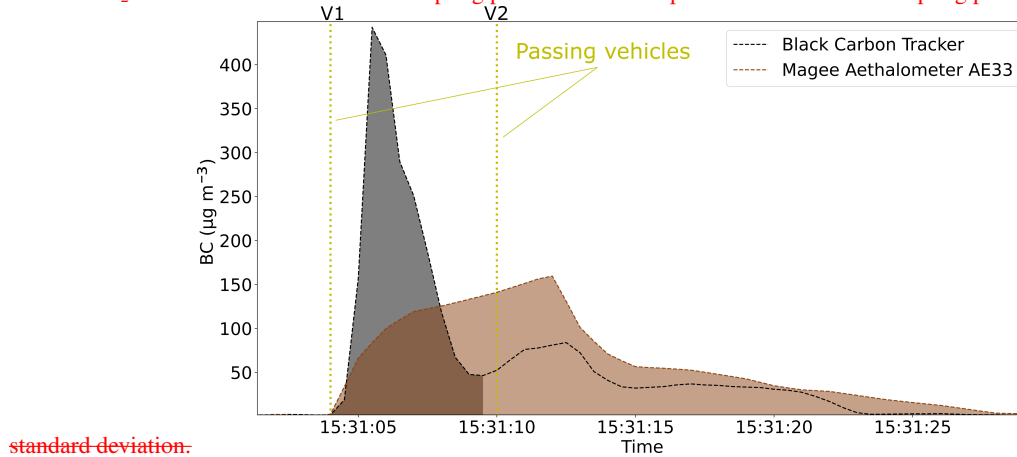
Figure 7. ~~Mean CO$_2$ concentrations (BG~~ Emission concentration ~~already subtracted~~time series example of two instruments with different response times. Gray (Black Carbon Tracker) and ~~mean capture rate for the three evaluated sampling positions~~ brown ~~(left, middle, right~~Magee Aethalometer AE33) shaded areas show the integrated areas of the BC emissions from the first passing vehicle as determined with the TUG-PDA.

485   – ~~Vehicle~~ and vehicle operating conditions (VSP)

    – Influence of environmental ~~conditions~~ and background conditions (see Appendix Sec. D)

    – Cross-interference from other pollution sources

In the following evaluations (e.g., Fig. 8, 9), we assess the influences of the above mentioned aspects on PS measurements. The results from the different measurement locations are labeled with numbers. Different sampling positions or traffic situations

490 were evaluated on individual locations. These are labeled with x.x (e.g., 1.1). This should facilitate the interpretation of the results and the comparison between the different impact factors, as they were not determined independently.

One selection criteria of PS campaigns is often the number of vehicles per site and day. Conducting campaigns on highly frequented roads guarantees a high number of vehicle passes. This is to a certain extent beneficial, as it allows for the collection of a large number of emission records. If the traffic density is too high for PS, the emissions from the individual passing vehicles

495 cannot be properly resolved because they superimpose (e.g. Fig. 5b). Not only the traffic density, but also the general traffic flow must be considered. Measurements are often performed after a crossroad or traffic light. Such conditions can lead to a high number of vehicles passing within a short period of time and a short distance ~~of~~ from each other. This prevents emissions from being properly resolved. Therefore, we evaluated the CR as a function of the median vehicle distance at different measurement locations. The CR generally increases with median vehicle distances at the measurement locations (Fig. ~~??). A smaller distance~~

500 ~~between the vehicles makes it more difficult to separate the emissions.~~ 8, left). It is noticeable that even in relatively dense traffic (median vehicle distances 3.3 - 6.2 s), a high CR (~~38~~ 31 - ~~47~~ 38 %) can be achieved if the sampling is done from the middle of the road.~~The time interval between the vehicle pass and the corresponding exhaust plume reaching the sample inlet is smaller~~

20

if the sample is extracted from the road center. At measurement location 6, we evaluated the CR for workdays (Fig. ??, 6.1) and weekends (Fig. ??, 6.2). During weekdays, the CR was rather low (26 %) with about 6.500 vehicles per day and a median vehicle distance of 2.5 s. On weekends, the traffic density was much lower with about 3000 vehicles per day and a median vehicle distance of 5.6 s, so that a significantly higher CR (35 %) could be achieved. Appendix ?? shows two dense traffic situations in which emissions for all passing vehicles can either be separated or not separated using the TUG-PDA. Higher CRs can be achieved when tests are performed for test vehicles or in isolated environments such as test tracks. Ježek et al. (2015) were able to capture 125 out of 150 plumes during test track experiments when sampling from the roadside. Wang et al. (2015) reported a CR of 70 % for roadside sampling and 46 % for sampling 15 m from the road for nighttime measurements with a test vehicle.

Capture rate as a function of the median vehicle distance at different measurement locations. The measurement locations are labeled by numbers. At measurement locations 3 and 7, the sampling was conducted from both the right side (3.1, 7.1) as well as from the center of the road (3.2, 7.1).

In order to select the measurement site, the road itself and the topography must be evaluated. We examined the influence of the VSP on the CR for the three sampling positions (left, middle, right). For this investigation, only speed, acceleration and the road gradient were used to calculate the VSP (see Appendix A3). The determined VSP values for the different measurement locations were are clustered and averaged. We observed only a small impact of the VSP on the CR (Fig. ??8, right). The CR increases slightly with increasing VSP regardless of the sampling position. A certain engine load (e.g., VSP > -5 kW t^{-1} according to Bernard et al. (2018)) is required for the measured vehicles, which can be accomplished in locations with a positive road gradient or at locations where vehicles accelerate (e.g. road crossings, slip roads). Measurements are often made after road crossings, where passing vehicles can be assumed to accelerate. This aspect should be critically assessed, since traffic conditions must be taken into account, as previously described. Roads with declining gradients should generally not be chosen due to lack of engine load. The road type must be considered in terms of space for the measurement setup and cross interference from other vehicles. In general, single-lane roads are preferred, as well as two-lane roads where the measured direction has a positive gradient. Vehicles driving on the opposite lane have a negative VSP and thus a low engine load. Along with the VSP, the width therefore only a small influence on the measurements.

The approach used to collect the exhaust has a major impact on the quality and strength of the signal. We found a direct relation between the CO_2 signal strength (see Fig. E1 in the Appendix) and the CR (Fig. 9, left). A higher CO_2 signal generally leads to a higher CR. The highest CR can be achieved if the sample extraction is performed from the middle of the roadhas a non-negligible impact on the sampling. When. By using this central setup, a CO_2 plume could be captured for an average of 34 % of the vehicles. Sampling from the left roadside delivers on average a CR of 25 % as compared to 17 % if the sample is extracted from the right side. In most regions in Europe, sampling from the side, the distance from passing vehicles strongly impacts the sample extraction due to increased dilution and greater dependability of tail pipe position or wind conditions. The CR as a function of the lane width is depicted in left is favored over the right side. Vehicles from manufacturers in Europe (e.g., VW, BMW, Mercedes, Fiat) have usually the tailpipe on the left-hand side, unlike manufacturers in Asia or the United States (e.g., Toyota, Kia). At two measurement locations (3 and 7), the sampling was conducted from both, the roadside and
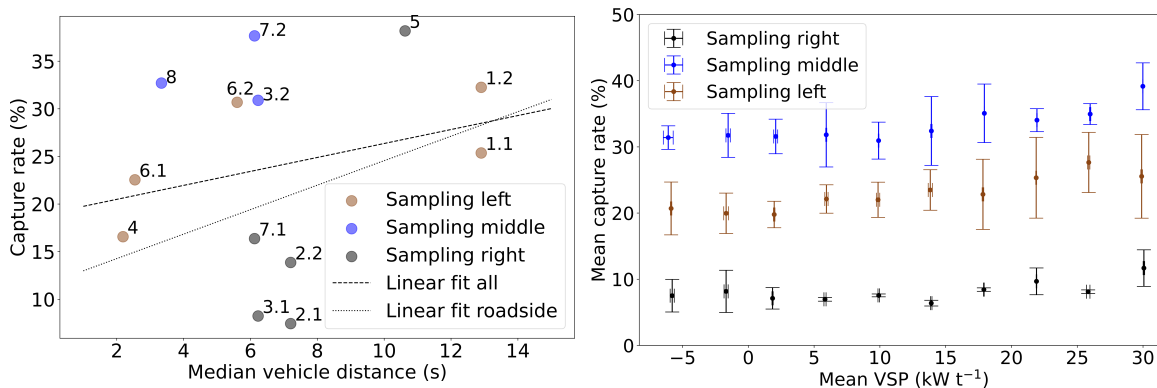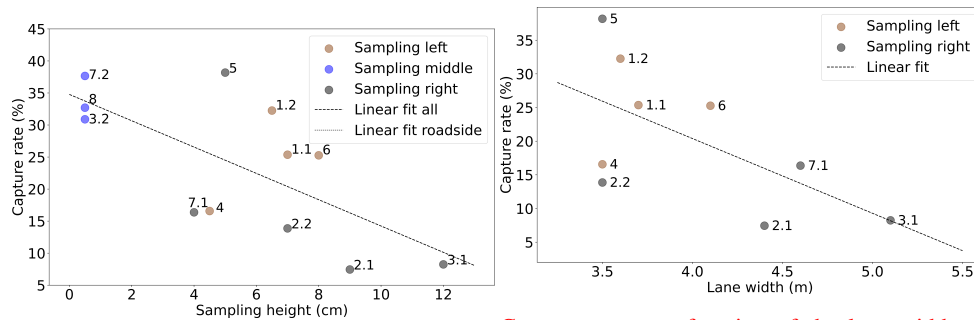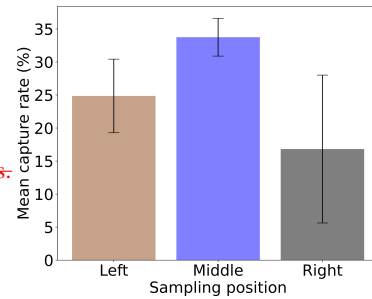
Figure 8. Evaluation of two traffic related impact factors and their influence on the capture rate. **Left:** The capture rate is shown as a function of the median vehicle distance at different measurement locations (indicated by numbers as in Fig. 9). **Right:** The calculated VSPs are clustered and shown separately for the different sampling positions.

from the center of the road. Two to three times higher CRs were obtained when sampling from the middle of the road (Fig. ~~??~~ ~~for measurement locations where the sample extraction was performed from the side~~ 9, middle and Fig. 8, left). Measurements

540 from the center of the road allows sample extraction in the closest proximity of the source and is therefore less influenced by traffic (Fig. 8, left), wind or tailpipe position. We found no significant influence on the driving behavior when the sampling was done from the center of the road through the covered tube. In addition to the influence of the sampling side, the sampling height also has a major impact on the sample extraction. Higher CRs and stronger CO_2 signals are achieved at lower sampling inlet heights for most vehicles in Europe. An exception are L-type vehicles (e.g. motorcycles) with tailpipes pointing straight

545 or even upwards. The width of the road ~~.~~ has a non-negligible impact on measurements from the roadside (Fig. 9, right). At two locations (1, 2), the sampling was conducted at two positions (1.1, 1.2 and 2.1, 2.2) at the same roadside with differences in road width and sampling height. For both, it can be seen that a smaller road width and a lower sampling height ~~(see Fig. ??)~~ lead to a higher CR. Measurement locations where the sampling was done from the right side (2, 3, 5, 7) generally have a rather low CR. An exception is location 5, where the highest CR of all measurement sites was achieved. Location 5 stands

550 out with good characteristics of all influencing factors such as a small lane width (3.5 m), a low sampling height (5 cm) and a high median vehicle distance of 10.6 s ($\sim$ 2.500 vehicle per day). ~~This highlights the importance of selecting appropriate measurement sites~~ The highest absolute number of valid measurements per hour was achieved at location 8 with 103 valid ERs per hour.

~~Different measurement locations may be accompanied with varying environmental conditions such as wind or BG concentrations~~

555 ~~of the measured species. In Fig. D1, 30-minute averaged BG concentrations for BC and CO₂ are shown for three different measurement sites over a time period of 24 hours. At Location 1, rather stable BC concentrations can be noted along with a distinct increase in the CO₂ concentration during the morning traffic period. In contrast, very high BC BG concentrations were measured at Location 4 on the presented measurement day accompanied by varying BG CO₂ values. Such different conditions depend on the season, meteorology, traffic density and other emission sources like industry and must be taken into~~

Figure 9. ~~Evaluation~~ Three plots show the influence of ~~two impact factors of~~ the ~~measurement location~~ sampling position and ~~their influence~~ road width on the capture rate. **Left:** Mean capture rate at the three sampling positions, combined from all measurement sites. **Middle:** Capture rate as a function of the height of the sampling inlet. The measurements were performed at different measurement locations, which are indicated by the numbers. **Right:** Capture rate as a function of the lane width for roadside measurements.

560   ~~account. High or varying BG concentrations can impact instrument performance. The BG concentration must be compensated for in the emission calculation and results can vary widely depending on the BG concentration used. In addition to using the concentration directly before the emission peak, two other approaches to determine BG values were evaluated. 1) A statistically determined BG values was calculated by removing emissions greater than the 75th percentile of the used dataset. A moving average filter was applied to the resulting dataset and the minimum valued was used as BG concentration. 2) Usage of a median~~

565   ~~or average BG concentration during the last time window when no vehicle was passing. The two approaches proved to be less accurate considering all measurement conditions.~~

     ~~Background concentrations of BC (upper plot) and CO$_2$ (lower plot) from three different measurement sites. Concentrations are averaged with a half-hour running mean filter.~~

3.2.3   Weather conditions

570   Harsh weather conditions can have a substantial impact on RES measurements. For both PS and RES, the literature lacks detailed assessments that examine the effects of environmental conditions. Of particular interest are the dependencies related to precipitation and wind conditions. ~~Commercial open-path RES systems have difficulties to measure during precipitation.~~

During the measurement campaigns, a weather station was either located directly next to the PS site or in the vicinity. The weather data used were available on at least hourly basis. To allow an unbiased comparison, only datasets were used where the

575 compared meteorological conditions were present during the measurement campaigns. ~~In Fig. ??, the CRs are compared during rainy and dry conditions~~

Rain: We found that the PS measurements were not significantly influenced by rain. CRs are comparable during rainy (29.3 %) and dry (29.8 %) conditions (Fig. 10, left). ~~On average, a slightly higher CR was determined in 36.7 % of the cases under dry conditions as compared to 36.2 % of the cases during rainy weather.~~ Similar values were also determined for the average CO_2

580 plume of the passing vehicles. During dry periods, an average CO_2 plume of ~~630 ppm~~ 525 ppm s was measured as compared to ~~631 ppm~~ 536 ppm s under wet conditions. We were particularly interested in discovering whether these conditions impacted PM emissions. For this purpose, we ~~compared the determined ERs for~~ performed a Monte Carlo simulation by drawing 100 samples of the measured ERs of the passing vehicles ~~regarding BC.~~ from the different measurement sites 1,000 times. We calculated the mean ERs from the 100 samples and the distribution of the mean values is shown in Fig. 10 in the right plot.

585 Statistically, no significant difference was observed between the ~~EFs calculated under dry or~~ ERs calculated in dry and rainy conditions with median values of 110 and ~~121 mg kg^{-1} CO_2, respectively (Fig. ??).~~ 134 mg (kg CO_2)$^{-1}$, respectively. The slight differences may result, for example, from different driving behavior in wet conditions.

~~Capture rate of CO_2 plumes.~~   ~~Mean BC ratio of the measured vehicles.~~
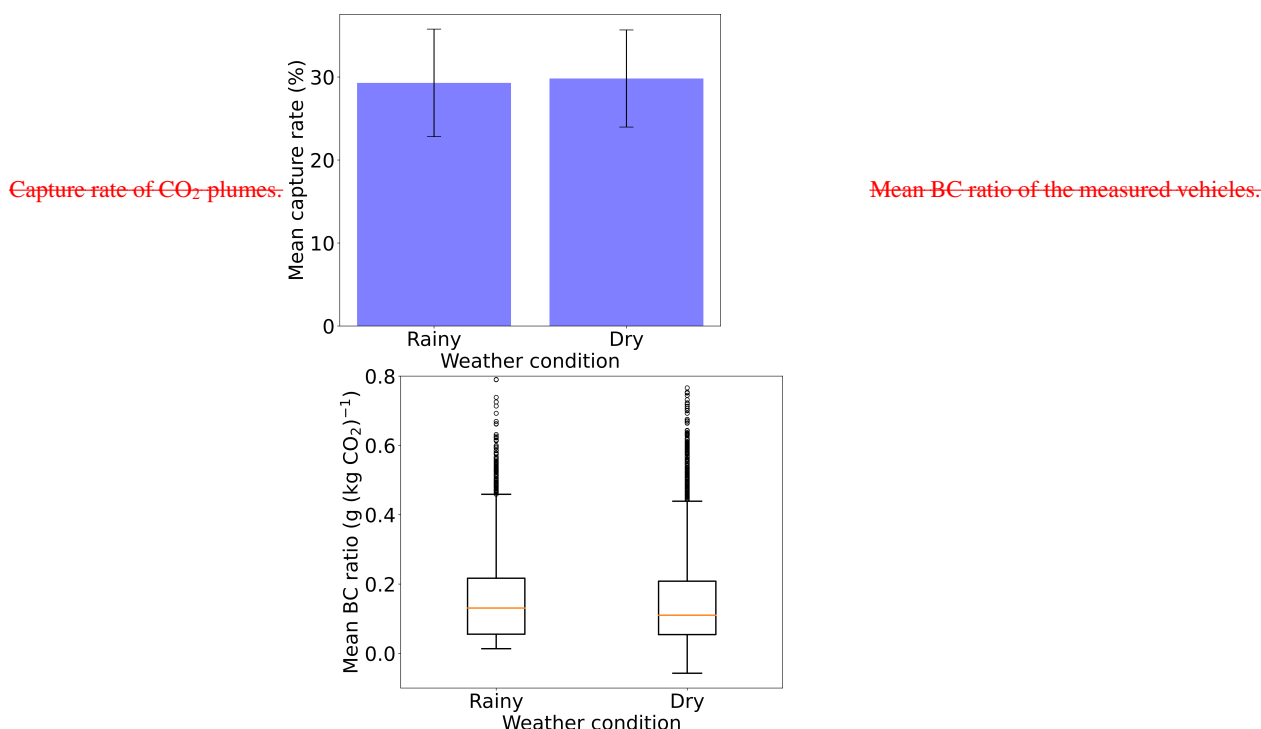
Figure 10. Effect of precipitation on PS measurements. Measurements are compared for rainy (> 0.05 mm h^{-1}) and dry weather conditions. Capture rates (**left**) and mean BC ratios (**right**) measured in both conditions are compared.

Wind: Wind direction and wind speed affect the dilution and transport of the plume. We assessed the effect of wind speed and wind direction on the measurements. The wind speed was segmented according to the Beaufort scale (Singleton, 2008).

590 ~~Under rather calm wind conditions (0-11 and 12-19 km h⁻¹, BFT 1,2 and 3), no significant impact could be observed. Under *moderate breeze* wind conditions (Beaufort scale, 20-28 km h⁻¹), a decrease in the CR is noticeable. This trend continues under *fresh breeze* conditions (29-38 km h⁻¹), although only measurements from one PS site for such conditions were available~~ (We found that with increasing wind speed the CR steadily decreases (Fig. ~~??). This trend shows that the CR generally decreases with increasing wind speed.~~ 11, left). A similar trend can be observed for the measured average CO_2 plume of the passing

595 vehicles. A higher CO_2 signal (~~684 ppm~~ 519 ppm s) was measured under calm conditions (< 20 km h⁻¹) than under windier (21-39 km h⁻¹) conditions (~~542 ppm~~ 425 ppm s). A similar influence of wind speed on the CR was reported by Dallmann et al. (2011) in their top-down PS study for HDVs. They reported lower CRs in June (61 % unsuccessful plume captures) than in November (36 % unsuccessful plume captures), where average wind speeds were twice as high. In contrast to our results, they found that the dilution of the captured plumes was similar for both wind conditions.

600 Not only the wind speed is relevant, but also the direction in which the wind blows the exhaust plume. We evaluated the impact of the wind direction on the PS measurements under calm (< 11 km h⁻¹) and breezier (> 11 km h⁻¹) ~~circumstances~~conditions. For this purpose, we separated the wind directions into wind blowing the exhaust plume towards the measurement location and wind blowing it away from the sampling point. The wind directions are indicated in Fig. F1 in the Appendix. A significant influence was observed at a rural measurement location (Fig. ~~??~~11, right). The CR is higher under calm conditions and when

605 winds are blowing towards the sampling position. We performed the same evaluation in urban environments. Here, we could not observe such a trend with similar CRs regardless of the wind direction (Fig. F2). We assume that this is mainly related to differences between the local wind conditions (local turbulences) directly at the PS spot and the wind measured at the weather station. Generally, wind conditions in street canyons are much calmer than those in open spaces, which is beneficial for PS applications.

610 **Temperature:** The influence of temperature is investigated in Fig. 12 for low (≤ 10 °C) and high temperatures (> 10 °C). Ambient temperatures ranged from -7.3 °C to 28.2 °C during the different measurement campaigns. No significant difference was observed with an average CR of ~~35.5~~ 28 % at low temperatures and of ~~35.9~~ 29 % at high temperatures. The effects of ambient temperature and humidity are not expected to have an impact on the PS measurement itself, if the instrumentation used are either properly stored or can perform measurements under such conditions. Ambient temperature is expected to have

615 an impact mainly on the passing vehicles and their exhaust after-treatment systems (Kwon et al., 2017; Ko et al., 2019).

3.2.4 ~~Instrument characteristics~~

~~Instrument characteristics (see Table 1) have a great influence on the quality of the measured emission data. Sugrue et al. (2020) compared high- and low-cost BC and CO_2 sensors for their application in PS. They found that low-cost CO_2 sensors may be an adequate substitute for research-grade analyzers in contrast to low-cost BC instruments. In their conclusion, they~~

620 ~~also emphasized that sensors should be tested under field-conditions. As an example, we compared characteristics of the custom-designed BCT with those of a commercially available Aethalometer AE33 (Magee Scientific). The Aethalometer~~
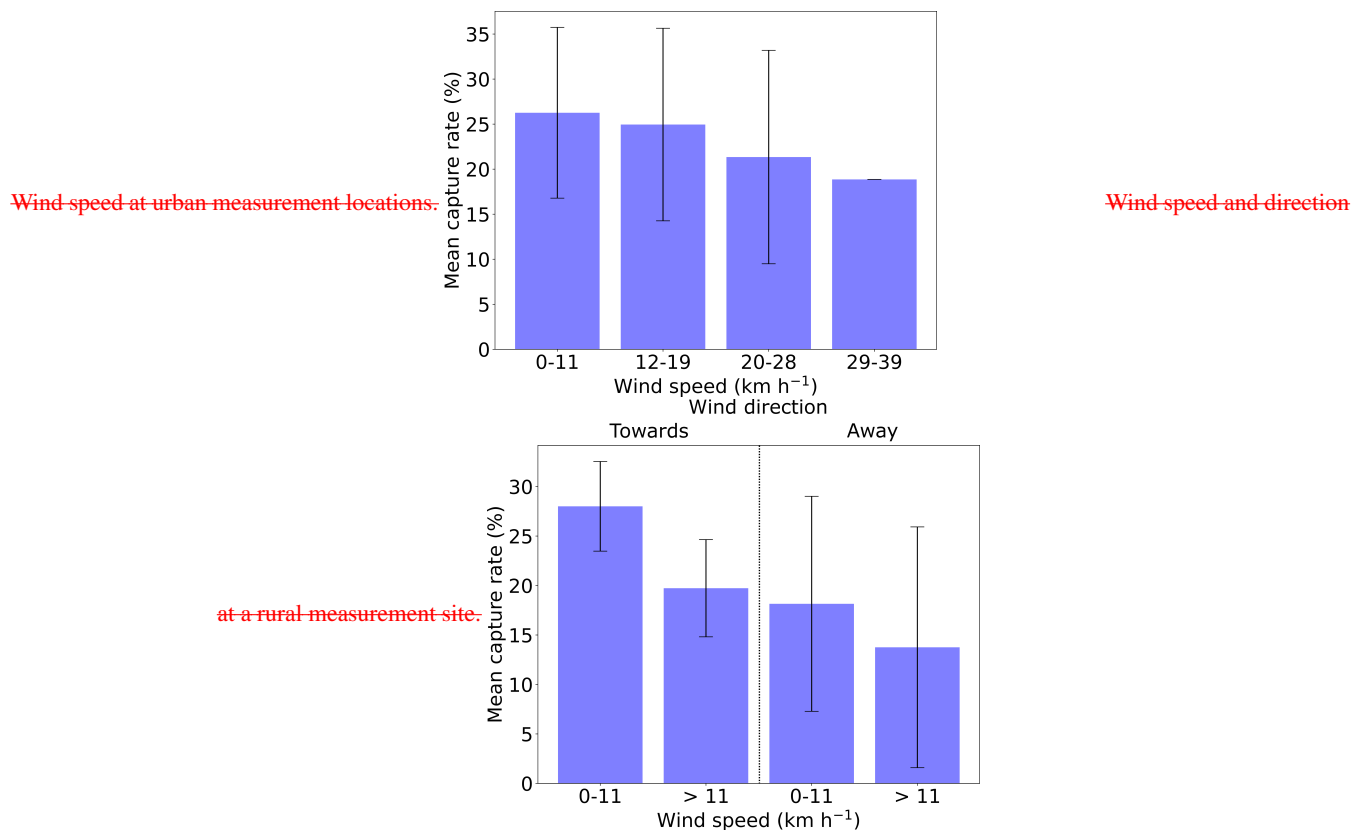
Figure 11. Influence of different wind conditions on the capture rate. **Left:** Wind speed at urban measurement locations. **Right:** Wind speed and direction at a rural measurement site.
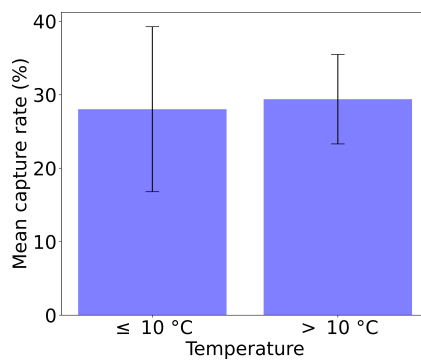

Figure 12. Influence of ambient temperature on the capture rate.

AE33 is widely used in environmental science for BC measurements and source appointment and is commonly used in PS studies to quantify BC emissions (Ježek et al., 2015; Preble et al., 2018; Zhou et al., 2020; Sugrue et al., 2020). Laboratory measurements showed a very good correlation ($R^2 = 0.99$) between the Aethalometer and the BCT. Comparable LoD ($3\,\sigma$)

3.3 ~~Application example~~

~~In~~

3.3 Measurement campaign

In total, for the city measurement campaigns in Italy, Poland and Czechia, it was possible to collect technical data from
645 authorities for 66,803 of the recorded vehicles. The technical data sets collected were pseudo-anonymised to comply with the data protection regulations of the individual countries. Based on the collected technical data sets, we determined with our data analysis framework (see Sect. 2.2) the emissions of ~~27,775[2]~~ 22,160 vehicles. Measurements were conducted with our described setup (see Sect. 2.1). Several instruments were used in the campaigns to measure BC, PN and NO$_x$ EFs. The newly developed BCT was used to measure BC and CO$_2$, a custom designed diffusion charger (Schriefl et al., 2020) measured
650 PN concentrations and an ICAD (Airyx GmbH, Horbanski et al. (2019)) was deployed for NO$_x$ and CO$_2$ measurements. A schematic of the emission measurement setup can be found in Appendix B.

3.3.1 Fleet composition and capture rate

The measurements were carried out in city centers, which is also reflected in the vehicle fleet. The vehicle types were classified according to the vehicle categories of the United Nations Economic Commission for Europe (UNECE). The largest share of

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[2] ~~23,430 excluding multiple passes of the same vehicles~~

655 vehicles measured were passenger cars (~~83.8~~ 84.1 %). A much smaller share of L-type vehicles (~~1.6~~ 1.4 %) and HDV and buses (0.8 %) were recorded (Fig. ~~??,~~ 13, left upper plot). We determined the CRs for the different vehicle categories to verify the ability to measure different vehicle types ~~.~~ (Fig. 13, left lower plots). The highest CR could be achieved for HDVs and buses (55 %), followed by passenger cars (~~35 %) . The CR of~~ 22 %) and L-type vehicles ~~, including motorcycles and scooters, was significantly lower with 27 % (Fig. ??, lower plots~~ (17 %). Previous PS studies (Dallmann et al., 2011, 2012) reported

660 CRs for HDVs using top-down measurements from a bridge and a tunnel. In these studies CRs ranged from 12 % to 59 % for individual trucks and from 16 % to 44 % for groups of trucks. In general, it can be said that the CR depends on the exhaust flow rate of the vehicles. HDVs and buses have much greater exhaust flow rates than passenger cars or L-type vehicles. This is also reflected when looking at the average integrated exhaust plume of the different vehicle categories. The average integrated exhaust plume of HDVs and buses (~~926~~ 947 ppm s CO_2) was significantly higher than those of passenger cars (~~519~~ 459 ppm

665 s CO_2) and L-type vehicles (~~327~~ 374 ppm s CO_2). A lower percentage of L-type vehicles is measured not only because of the smaller exhaust flow rate, but also because of the direction of the exhaust pipe. In contrast to HDVs, buses and passenger cars, the exhaust pipe for L-type vehicles often points upwards, which is disadvantageous when sampling from low heights. Looking at the distribution of the fuel type of the measured vehicles, a similar number of diesel (~~45.5~~ 45.2 %) and petrol (~~45.8~~ 46.5 %) vehicles were measured. A small share of CNG, LPG or bi-fuel (petrol/diesel + CNG/LPG, ~~2.5~~ 2.6 %) was captured (Fig. ~~??,~~

670 13, right upper plot). In contrast to the vehicle type, the CR is rather independent of the fuel type (Fig. ~~??,~~ 13, right lower plot). EFs could be determined for ~~35~~ 24 % of diesel vehicles, which ~~represents a~~ is slightly higher CR compared to ~~34 % of the petrol vehiclesmeasured~~ 22 % of petrol vehicles. This is mainly due to the fact that vehicles with a larger engine displacement (e.g. trucks or buses) are mostly powered by diesel engines, while smaller vehicles are mostly equipped with petrol engines (e.g. L-type vehicles).

675 ### 3.3.2 Fleet emission characteristics

Fuel-based EFs (see Appendix A1) were determined for the measured vehicles using the collected technical vehicle data. The fuel-based EF accounts for the larger total emissions from large vehicles such as HDVs and buses and makes all derived EFs comparable. Statistical evaluations were carried out for various vehicle categories and Euro emission standards (Fig. 14 to Fig. 16). Upper and lower whiskers represent the 97.5 and 2.5 percentile, respectively. The number of vehicles in each category

680 is indicated by the numbers in the brackets. Emissions from hybrid electric vehicles are included in the statistics. There are mainly two reasons for negative EFs. First, negative EFs result from low emitting vehicles where the determined background is higher than the measured emissions during the captured CO_2 plume. Second, the emissions of ~~previously passing~~ other vehicles interfere with the measurement of the current vehicle.

BC emissions from ~~petrol~~ petrol-powered passenger cars (M1 category) decrease ~~slightly~~ from Euro 2 to Euro 6 emission

685 standards ~~, with mean values between 87~~ . The mean values decreased from 256 to 103 mg (kg fuel)$^{-1}$ and ~~150 mg kg^{-1} fuel~~ and median values ~~ranging from 10.1 to 16.5~~ decreased from 57 to 37 mg (kg fuel)$^{-1}$. For ~~diesel passenger cars~~ passenger cars with diesel engine, BC emissions decrease significantly with increasing Euro emission standards and decreasing vehicle age from ~~1.82~~ 2.37 g (kg fuel)$^{-1}$ (median: ~~0.87~~ 1.08 g (kg fuel)$^{-1}$) for Euro 2 down to ~~0.078 g~~ 81 mg (kg fuel)$^{-1}$ (median: ~~7~~ 30 mg (kg
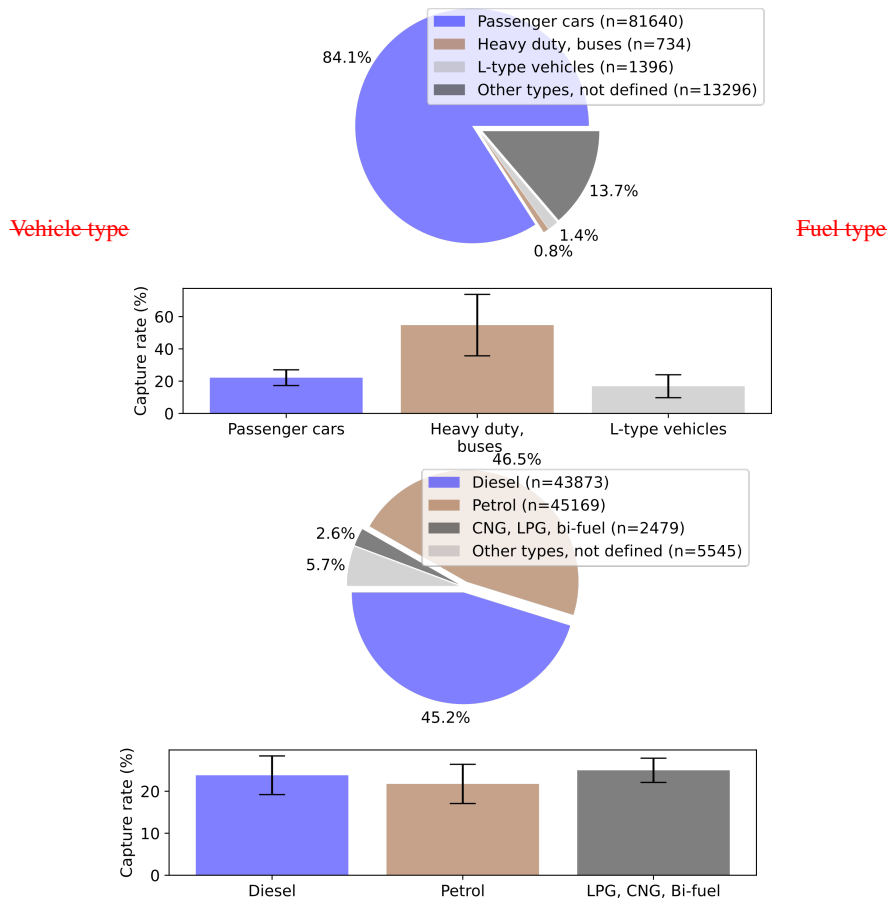
28

Figure 13. Measured ~~vehicles~~ vehicle fleet split into vehicle categories (**left**) and fuel type (~~upper plots~~**right**). Capture rates for the different types are shown in the lower plots. The data contains multiple passes of the same vehicles.

fuel)$^{-1}$) for Euro 6. This corresponds to a reduction by a factor of more than 30 from Euro 2 to Euro 6 on the median. The impact of the introduction of DPFs sticks out from Euro 5 onwards. ~~Median BC emissions drop by a factor of 15 from Euro 4 to Euro 5 vehicles, from 0.19 to 0.013 g (kg fuel)$^{-1}$. Emissions from Euro~~ BC emissions from Euro 6 diesel vehicles are ~~in the range~~ below of those from Euro 6 petrol vehicles. Similar trends can be observed for BC emissions of HDVs and buses. The BC EFs of both HDVs and buses drop significantly from Euro III to ~~IV and from Euro IV to~~ Euro V. Measured buses were mainly well maintained city operated Euro V and VI vehicles, with BC emissions ~~in the range~~ even lower than those of Euro 6 passenger cars.

PN measurements were performed for particles ~~greater~~ larger than 23 nm (D_{50} cut-off at 23 nm) using a catalytic stripper to remove volatile compounds (Giechaskiel et al., 2014). PN and BC results agree well for the different vehicle categories and Euro emission standards, as only the solid particle fraction was measured (Fig. 15). The impact of the introduction of DPF for diesel passenger cars is even more pronounced for PN than for BC. Median PN EFs decrease from Euro ~~4 to Euro 5 from 320~~
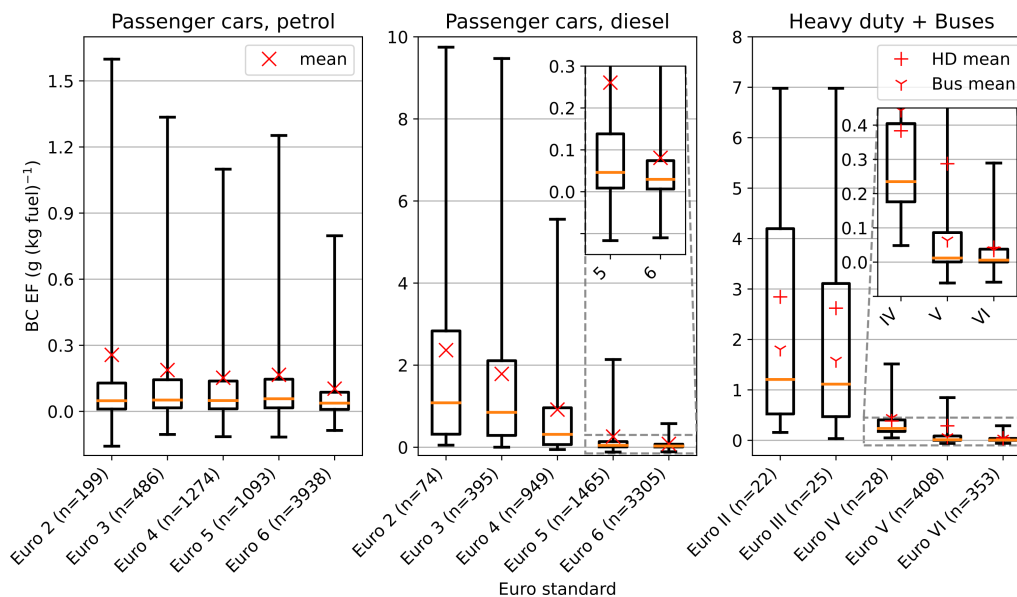
Figure 14. Distribution of fuel-based BC EFs in dependence of the Euro emission standard for different vehicle categories. Passenger cars are split into petrol and diesel-powered vehicles. The numbers in brackets represent the sample size.

700   ~~to 11~~ 2 to Euro 6 from 1,842 to 22 · 10^{12} particles per kg fuel by a factor of ~~29.~~ more than 80. The greater reduction of PN compared to BC EFs can be related to DPF filtration efficiency, which depends on the particle size distribution (Yang et al., 2009; Rossomando et al., 2021). Vehicle exhaust PN consists mainly of a large number of small particles below 60 nm, while the main contributor to BC mass concentration are accumulation mode particles (Giechaskiel et al., 2014). However, a shift towards smaller particles sizes caused by newer engine technologies must be taken into account.

705   NO_x emission levels of ~~petrol~~ petrol-powered passenger cars are steadily decreasing from Euro 2 to Euro 6 (Fig. 16). Median values decrease from ~~3.52~~ 5.74 g (kg fuel)$^{-1}$ to ~~0.22~~ 0.87 g (kg fuel)$^{-1}$. The effects of "Dieselgate" are reflected in the NO_x emissions of diesel passenger cars, which primarily affect Euro 5 and Euro 6 vehicles. NO_x EFs stagnate for Euro 2 to 5 vehicles, with median values ranging from ~~8.24 to 9.16~~ 9.78 to 13.31 g (kg fuel)$^{-1}$. For Euro 6 vehicles, NO_x EFs decrease significantly with a median value of ~~1.74~~ 2.85 g (kg fuel)$^{-1}$. In contrast to BC and PN, NO_x EFs for HDVs and buses are higher

710   compared to ~~the~~ emissions of passenger cars. This applies to all Euro classes. HDVs tend to have a higher milage, which affects the deterioration of the vehicle's condition. In addition, intentional tampering of the NO_x reduction system is believed to be more common in commercial vehicles than in private vehicles.

Table 3 compares average emissions of selected Euro emission standards from this study with previous open-path RES and PS studies. The average BC EFs from this study are compared with the PM EFs from other studies. BC can be assumed to be a

715   subset of PM. For diesel vehicles, BC typically accounts for the largest share of PM emissions. This is especially the case for older Euro emission standards and vehicles with defective DPF. The proportion of BC emissions for petrol vehicles is typically
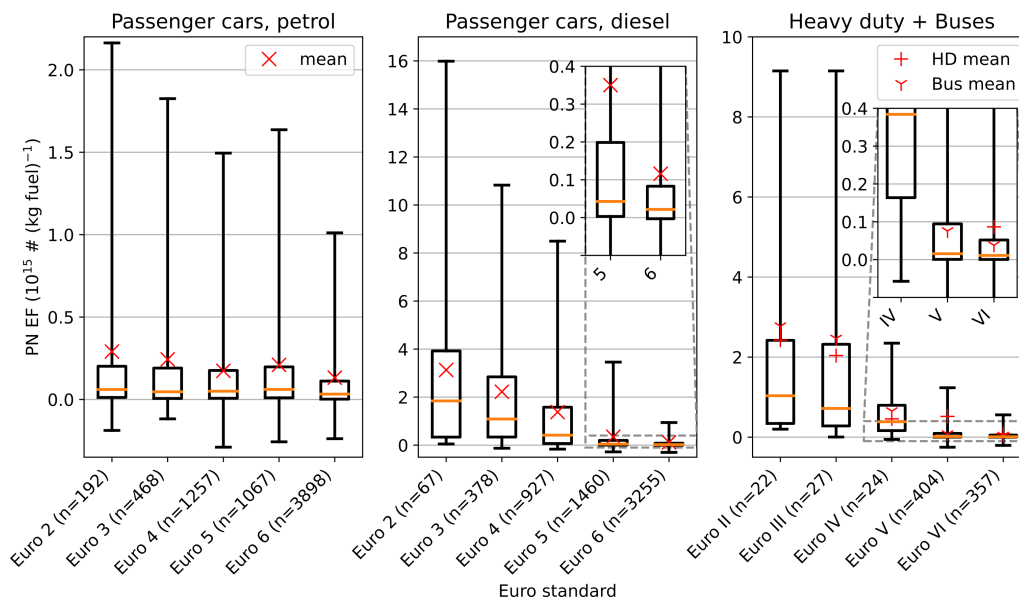
Figure 15. Distribution of fuel-based PN EFs in dependence of the Euro emission standard for different vehicle categories. PN measurements were performed for solid particles greater than 23 nm (SPN$_{23}$). Passenger cars are split into petrol and diesel-powered vehicles. The numbers in brackets represent the sample size.
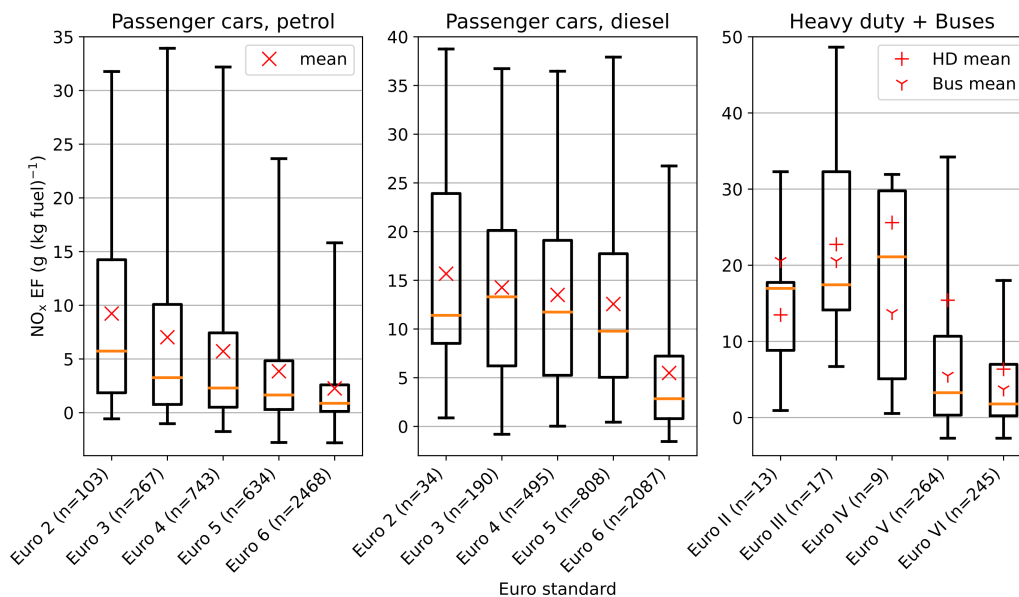

Figure 16. Distribution of fuel-based NO$_x$ EFs in dependence of the Euro emission standard for different vehicle categories. Passenger cars are split into petrol and diesel-powered vehicles. The numbers in brackets represent the sample size.

lower, except under specific conditions (Platt et al., 2017; Yang et al., 2019; Bessagnet et al., 2022). PN EFs are reported only for PS studies, because only rough estimates from open-path RES studies can be made for PN.

Average BC EFs from this study and PM EFs from open-path studies are in a similar range for petrol and diesel passenger cars. The average PM EFs reported from open-path RES studies are subject to a large variation. The measured emissions can vary widely depending on several factors such as fleet characteristics (e.g. vehicle type, manufacturer, mileage, age) or the measurement location. Determined average BC EFs from this study for Euro 5 and 6 passenger cars are higher than those found in open-path RES studies. One reason for this can be the quantification limit of open-path RES instruments for PM measurements. Several studies pointed out difficulties in quantifying emissions of newer Euro emission standards, which was reflected in negative average EFs (Gruening et al., 2019; Cha and Sjödin, 2022; Jerksjö et al., 2022). The average NO$_x$ EFs from the selected open-path RES studies vary to a much smaller extent. Determined NO$_x$ EFs for ~~petrol~~ passenger cars of this study agree well with literature values for almost all Euro emission standards given. ~~NO$_x$ emissions from diesel passenger cars are lower compared to those presented in literature studies. This could be due to peculiarities in the composition of the vehicle fleet, vehicle updates after "Dieselgate" creating a change in the fleet or due to differences in the measurement principles. Validation studies (Ropkins et al., 2017; Sjödin et al., 2018; Gruening et al., 2019) show a very good agreement between reference measurements with portable emission measurement systems (PEMS) and open-path RES for NO measurements. The studies found differences in absolute values between PEMS and open-path RES systems, with open-path RES systems partially underestimating NO EFs. Differences could also be due to determined NO$_2$ EFs, where higher inaccuracies were reported for open-path RES. These could come from concentrations below the quantification limit of open-path RES systems and the volatility of the gas. For PS, detailed validation studies are not available yet. Ježek et al. (2015) reported a good agreement of average BC EFs between PS and PC methods. Larger deviations were reported for the measured PN EFs of the two methods, which could be due to higher uncertainties resulting from PN measurements including volatile compounds.The~~

The calculated EFs of HDVs and buses from this study are compared with selected literature from both PS studies and open-path RES studies. The selected PS studies were conducted solely in Sweden. BC EFs of this study and PM EFs of literature studies are in similar ranges for Euro III to Euro V standards. Differences are mainly observed for Euro VI HDVs. These can arise from differences in fleet characteristics or vehicle age, causing deterioration of the exhaust after-treatment system. This could be particularly the case for newer Euro VI HDVs, where 2-3 years between the studies can have a significant impact. Negative PM EFs reported by open-path RES studies can be referred to limits in instrument accuracy similar to those for passenger cars. PN EFs for HDVs and buses reported in previous PS studies are generally higher than those reported in this study. This can be attributed to the different size characteristics of the used PN instruments. Particles larger than 5.6 nm were measured by Hallquist et al. (2013), Liu et al. (2019) and Zhou et al. (2020). In this study, the D$_{50}$ cut-off was 23 nm (Schriefl et al., 2020). We ~~used SPN~~performed solid particle number (SPN) measurements with a cut-off at 23 nm to comply with current emission regulations and to be able to relate the calculated EFs to official limits. Determined NO$_x$ EFs of HDV and buses are in good agreement with literature data of PS and open-path RES studies. Similar to diesel passenger cars, NO$_x$ EFs of this study for HDV and buses are slightly lower compared to literature data of open-path RES studies. NO$_x$ EFs of

literature PS studies span over a wide range, which can be referred to differences in vehicle exhaust after-treatment systems. In Hallquist et al. (2013), open-path RES data was used to determine NO_x EFs. Which EFs are more accurate ~~can not~~ cannot be judged from the comparison as several reasons influence the derived EFs like measurement location, vehicle fleet, driving

755　properties, environmental conditions, instrument characteristics or data analysis ~~algorithm~~methods. A detailed comparison of our PS system with other simultaneous measurements will be part of a separate study.

4　Summary and conclusions

This paper presents a PS system capable of ~~continuously screening entire vehicle fleets~~ screening vehicle fleets largely independent of the vehicle type. Our approach allows the direct measurement of different particle metrics such as BC or

760　PN as well as different gaseous compounds (e.g. NO_x). In particular, PN is a relevant metric today with knowledge of the health effects of ultrafine particles (Oberdörster et al., 2005; Brook et al., 2010; Mannucci et al., 2015), but also concerning currently introduced emission legislations (Bainschab et al., 2020; Giechaskiel et al., 2021). Newly introduced Euro emission standards bring along stringent requirements, where current open-path RES systems reach their quantification limits, especially for PM (Gruening et al., 2019; Cha and Sjödin, 2022; Jerksjö et al., 2022). Compared to commercial open-path RES systems,

765　the installation of the PS measurement setup is relatively simple. The method is quite flexible when it comes to where the sample extraction is performed and what instruments are used to measure the species of interest. We presented a comprehensive data analysis framework that is capable of processing emissions from ~~1,000s~~thousands of vehicles. ~~This encompasses the pre-processing of raw time series of instruments to the post-analysis of emission statistics of whole vehicle fleets. The core of this software~~ The core is the TUG-PDA, which determines and separates vehicle emissions down to a distance of 3 s between

770　the vehicles, if appropriate instruments are used. ~~The data analysis provides the capability to analyze emissions for different vehicle characteristics such as emission standard, age, mileage or manufacturer. This allows detailed analysis of emission patterns to investigate whether emission standards are being met and also helps to identify the causes of high emissions.~~ We have shown that emissions from overlapping plumes can be measured with similar accuracy as when there is no overlap. As an application example, we presented the first results of measurement campaigns in three different European cities in which

775　we made use of our PS method. We showed distributions of measured BC, PN and NO_x EFs of different vehicle types and Euro emission standards. The results are in good agreement with relevant literature studies and ~~showed~~ show the potential for screening emissions of ~~vehicles with~~ different vehicle types, including those meeting newly introduced emission standards.

　　We evaluated important impact factors influencing PS measurements ~~, which~~ that should be considered when planning and implementing PS campaigns. ~~As our evaluations show, the CR can vary greatly depending on the different factors.~~ The most

780　important influences are summarized in the following:

- Instruments used for PS campaigns should be properly chosen (see Table 1). Response time, dynamic range and ~~LoD~~ limit of detection are the most significant factors. The response time should be as low as possible (< 1-2 s). The dynamic range should be large enough to cover both low and high emitters. The ~~LoD~~ limit of detection should be low enough to accurately determine the emissions from the evaluated species.

Study	Vehicle type - fuel type	Euro standard	Av. EF BC/PM mg (kg fuel)$^{-1}$	Av. EF PN 10^{12} # (kg fuel)$^{-1}$	Av. EF NO$_x$ g (kg fuel)$^{-1}$
This study	Passenger cars - petrol	Euro 3	~~124~~188[a]	~~180~~243[c]	~~5.7~~7.0
Open-path RES studies[1,2,3,4]			30 - 670[b]	-	5.1 - 14.5
This study		Euro 4	~~127~~153[a]	~~182~~174[c]	~~4.4~~5.7
Open-path RES studies[1,2,3,4]			20 - 200[b]	-	3.8 - 7.2
This study		Euro 5	~~137~~166[a]	~~214~~210[c]	~~3.0~~3.9
Open-path RES studies[1,2,3,4]			30 - 90[b]	-	2.5 - 3.3
This study		Euro 6	~~97~~103[a]	~~139~~132[c]	~~2.1~~2.3
Open-path RES studies[1,2,3,4]			0 - 95[b]	-	-0.5 - 3.2
This study	Passenger cars - diesel	Euro 3	~~1470~~1787[a]	~~1813~~2223[c]	~~10.0~~14.3
Open-path RES studies[1,2,3,4]			170 - 1840[b]	-	13.7 - 18.7
This study		Euro 4	~~749~~918[a]	~~1185~~1377[c]	~~10.5~~13.5
Open-path RES studies[1,2,3,4]			130 - 1080[b]	-	11.6 - 15.4
This study		Euro 5	~~201~~261[a]	~~294~~351[c]	~~10.2~~12.6
Open-path RES studies[1,2,3,4]			20 - 270[b]	-	11.7 - 14.4
This study		Euro 6	~~80~~81[a]	~~116~~117[c]	~~6.8~~5.5
Open-path RES studies[1,2,3,4]			10 - 70[b]	-	5.8 - 8.5
This study	Buses, heavy duty - diesel	Euro III	~~1476, 1985~~1579, 2620[a]	~~2078, 2585~~2465, 2039[c]	~~18.3, 19.2~~20.6, 22
PS studies[6,7,8]			30 - 1820[b]	730 - 3900[d]	16 - 43.3[e]
Open-path RES studies[1,4]			250 - 2100[b]	-	24.6 - 27.5
This study		Euro IV	~~259, 561~~443, 384[a]	~~285, 1575~~651, 458[c]	~~20.7, 16.7~~13.7, 25
PS studies[6,8]			172 - 1845[b]	870 - 3200[d]	14 - 19.8[e]
Open-path RES studies[1,4,5]			220 - 1250[b]	-	17.8 - 21.5
This study		Euro V	~~67, 280~~63, 287[a]	~~102, 498~~77, 520[c]	~~5.6, 12.8~~5.5, 15.
PS studies[6,7,8]			146 - 258[b]	650 - 1600[d]	15 - 37[e]
Open-path RES studies[1,2,4,5]			40 - 360[b]	-	13.1 - 25.3
This study		Euro VI	~~45, 88~~35, 43[a]	~~67, 154~~38, 87[c]	~~4.3, 5.7~~3.7, 6.4
PS studies[8]			5[b]	850[d]	3.1
Open-path RES studies[1,2,4,5]			-50 - 190[b]	-	2.8 - 8.7

Table 3. Comparison of average fuel-based BC/PM, PN and NO$_x$ EFs of this study with selected open-path RES and PS literature data. Emissions are ordered by vehicle category, fuel type and Euro emission standard. BC/PM column show either BC or PM EFs. [1]Hooftman et al. (2019), [2]Bernard et al. (2021), [3]Jerksjö et al. (2022), [4]Cha and Sjödin (2022), [5]Lee et al. (2022), [6]Hallquist et al. (2013), [7]Liu et al. (2019), [8]Zhou et al. (2020), [a]BC, [b]PM, [c]PN > 23 nm, [d]PN > 5.6 nm, [e]NO EFs of Hallquist et al. (2013) were determined by open-path RES, NO$_2$ measurements are estimated.

785   – When selecting the measurement site, the traffic conditions must be taken into account. An ideal condition is a steady traffic flow with sufficient distance (≥ 3 s with appropriate instrumentation) between the vehicles to collect a high number of valid emission records. At the measurement site, the passing vehicles should be under considerable engine load. This can either be in appropriate traffic situations where vehicles accelerate (e.g., after crossing, slip road) or at roads with positive gradients.

790   – The sampling should be performed as close to the exhaust source (~~tail pipe~~tailpipe) as possible. The best results can be achieved if the sample extraction is performed from the middle of the road with the sampling tube directly attached to the road. When sampling from the side, the road width (smaller roads preferred) and the sampling height (as low as possible) have a significant influence on the CR. In addition, the position of the exhaust pipe of the fleet of interest should be examined in advance to determine the best sampling position.

795   – The CR depends on the wind speed and direction. Windy conditions that transport the exhaust plume away from the sampling point have a negative effect on the CR. The influence of wind can be minimized by choosing an appropriate measurement location (e.g., street canyon). Other weather factors such as temperature or precipitation have negligible impact.

    – ~~The impact of harsh and varying BG conditions on the instruments, as well as on the data analysis, must be considered.~~

800   ~~Local (directly before the vehicle pass) BG concentrations should be used to minimize calculation errors. Differences in the BG determination have a large influence on the resulting EFs for low emitters and highly diluted plumes.~~

    – ~~Care should be taken to align the measured time series data. Misalignments between the response time (i.e. between the vehicle pass time and instruments) or between sensors (CO_2 and pollutants) can cause substantial errors. This can already be the case for time shifts of 1-2 s.~~

805   Future work will involve a detailed analysis of the gathered BC, PN, and NO_x emissions. Several open questions will be addressed such as how PS measurements relate to those made by reference equipment such as PEMS or other ~~methods.~~ RES methods (Knoll et al., In preparation). Further development of the TUG-PDA could address improvements in the determination of BG for overlapping plumes (e.g. using a linear approximation between the start and end of the peak) or the use of adaptive thresholds and parameters depending on the measurement location. Another interesting aspect to ~~be investigated~~ investigate

810 is the reproducibility and reliability of individual measurements. This is particularly important for the potential identification of high emitters. Commercial open-path RES systems are associated with a high degree of uncertainty when considering individual measurements (Huang et al., 2020; Qiu and Borken-Kleefeld, 2022). PS results indicate that single measurements are more reliable due to the longer measurement duration. It would be a great ~~advance~~ step forward if this could be proven and applied in the future to identify individual high emitters.

Appendix A: Remote emission sensing definitions

A1 Emission ratio and fuel-based emission factor

Emissions of combustion-based vehicles are generally reported as EFs. In RES, fuel-based EFs are used to express emissions from the measured vehicles (Hansen and Rosen, 1990; Borken-Kleefeld et al., 2018; Bernard et al., 2018). Fuel-based emissions are expressed as a mass fraction of the emitted pollutant per mass of burned fuel. The amount of burned fuel is calculated based on the measured CO_2 concentration of the passing vehicle by using the carbon mass balance method (Bishop et al., 1989; Hansen and Rosen, 1990; Stedman et al., 1992; Singer and Harley, 1996; Ban-Weiss et al., 2009; Hak et al., 2009) and under the assumption that the majority (> 90 %) of the carbon content in the fuel is oxidized to CO_2 during the combustion process. By relating the measured pollutant P (e.g., BC, PN, NO_x) to the measured CO_2 concentration, an ER can first be calculated (Stedman et al., 1992; Hansen and Rosen, 1990):

$$ER = \frac{\int_{t_1}^{t_2}([P]_t - [P]_{t_0})dt}{\int_{t_1}^{t_2}([CO_2]_t - [CO_2]_{t_0})dt} \tag{A1}$$

By multiplying the ER with the mass fraction of carbon in fuel ω_c a fuel-based emission factor EF_{fb} (Ban-Weiss et al., 2009; Hak et al., 2009) can be calculated:

$$EF_{fb} = ER \cdot \omega_c, \tag{A2}$$

where ω_c discriminates among different fuel types (see Table A1). Regarding PS measurements, the emission events last for several seconds. The measured concentrations of the pollutant and CO_2 for one vehicle pass are commonly integrated and the results are related to each other. The start and stop times of the emission event define the integration intervals and these are represented by t_1 and t_2, respectively. The measured emissions are superimposed by BG concentrations of the different species in ambient air. For that reason, a BG correction is required, where t_0 specifies the point of time from which the BG concentration is used. The BG is usually determined on the basis of the concentration at the integration starting point, t_1. When plumes overlap or impacts from other sources occur, this concentration may be underestimated.

Fuel type	ω_c
Gasoline (2016 E0)	0.864
Diesel (B0)	0.861
CNG	0.708-0.717
LPG	0.824
LNG	0.749-0.756

Table A1. Typical mass fraction of carbon in common fuel types from JRC (2020).

A2   Distance-based emission factor

Fuel-based EFs do not distinguish between vehicles with different fuel consumption. Therefore, fuel-based EFs favor vehicles with higher fuel consumption. Distance-based EFs, on the contrary, include the fuel consumption and are, therefore, usually used to compare vehicle emissions (Bernard et al., 2018). However, distance-based EFs cannot be directly calculated in RES due to the snapshot measurement. An estimate can be calculated using the type approval CO_2 consumption (Avg_{CO_2}) which is obtained from the vehicle technical information. The official CO_2 emissions from passenger cars have been shown to differ increasingly from real-world emissions (Tietge et al., 2017). Therefore, a correction factor (RWG_{CO_2}) including the real-world CO_2 gap can be included according to Bernard et al. (2018). Making this assumption, a distance-based EF can be calculated as follows:

$$EF_{db} = ER \cdot Avg_{CO_2} \cdot RWG_{CO_2} \tag{A3}$$

In a recent publication by Davison et al. (2020), a new approach was presented to calculate the distance-based EF in RES studies using the VSP. A good agreement was found between the outcome of their approach and validation measurements made with portable emission measurement systems (PEMS).

A3   Vehicle specific power

VSP is often used when performing emission modeling of combustion-based vehicles to estimate vehicle operating conditions. Using VSP, insights can be gained to estimate the engine load when a vehicle passes the measurement point. For example, this can be used to exclude vehicles with a small VSP ($< $ -5 kW t^{-1}) due to the disabled fuel injection in the engine (and therefore unexpected CO_2 emissions) (Bernard et al., 2018). The VSP is defined according to Jimenez-Palacios (1999) by the sum of the relevant power variables related to the mass of the vehicle:

$$VSP = \frac{\frac{d}{dt}(E_{Kin} + E_{Pot}) + F_{Rol} \cdot v + F_{Aero} \cdot v}{m} = v \cdot \left(a \cdot (1+\epsilon) + g \cdot grade + g \cdot C_R + \frac{1}{2} \cdot \rho_a \cdot C_D \frac{A}{m} \cdot (v + v_w)^2\right) \tag{A4}$$

Where E_{Kin} and E_{Pot} are the kinetic and the potential energies, respectively, v is the speed of the vehicle, F_{Rol} is the force from the rolling friction, F_{Aero} is the aerodynamic drag force, m is the mass of the vehicle, a is the vehicle acceleration, ε is the mass factor, g is the gravity of Earth, $grade$ is the road gradient, C_R is the coefficient of the rolling resistance, ρ_a is the density of ambient air, C_D is the drag coefficient, A is the projected frontal area of the vehicle and v_w is the headwind impacting the vehicle.

Appendix B: PS emission measurement setup

Fig. B1 shows the emission measurement setup used during one of the measurement campaigns. A water protection hose protected the sampling inlets from water. Two different sampling tubes were used for particle and gas sampling. Tygon tubing

with a inner diameter of 5 mm was used for particle sampling. Teflon tubes were used for the NO_x measurements, due to the
volatility of the gas. Both sampling paths were protected with water traps. For the particle measurements, impactors removed
particles with diameters greater than 1 μm. BC and CO_2 were measured with the newly developed BCT (Knoll et al., 2021).
In parallel measured an Aethalometer AE33 (Magee Scientific) BC and brown carbon (BrC). Total particle number (TPN)
concentration was measured using a CPC (Condensation Particle Counter 3775, TSI Incorporated). ~~SPN measurements were
conducted~~ Solid particle number (SPN) measurements of particles larger than 23 nm were performed with a diffusion charger
(Schriefl et al., 2020) downstream to a custom-built catalytic stripper which removed volatile compounds. A second BCT
measured in parallel to the diffusion charger BC and CO_2. A dust filter protected the instrument in the gas sampling path from
particle penetration. NO_x and CO_2 were measured with an ICAD (Airyx GmbH, Horbanski et al. (2019)).
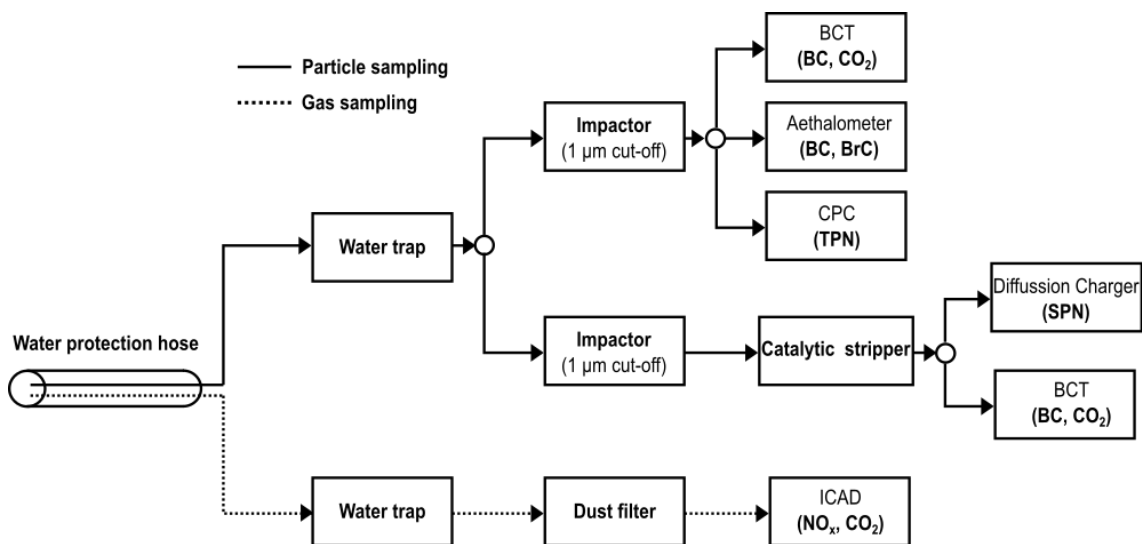
Figure B1. PS emission measurement setup used during one of the campaigns.

Appendix C: TUG-PDA emission separation capabilities

Fig. ~~5a and Fig. 5b show two PS time series examples that demonstrate the capabilities and the limits of the TUG-PDA
for plume separation of passing vehicles. Four vehicles passed by the PS spot, as shown in the data presented in~~ C1 shows
the influence of interference, but additionally includes the superposition of the measured BC emissions to the superposition
of CO_2 emissions. The emission distributions are separated in the same manner as in Fig. ~~5a. The TUG-PDA detects the
rising concentrations (increasing gradient) of BC and CO_2 when the first vehicle (V1) passes and integrates the areas (A1)
until the determined CO_2 BG concentration is undercut. When the second vehicle passed (V2), a much weaker plume was
captured and only a minor increase in both CO_2 and BC (A2) can be detected. The mean value of the turning point from~~

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negative to positive gradient, and a concentration value from the last time window where no vehicle passed is used as BG concentration. Four seconds after the second passage, a third vehicle (V3) passed by. A substantial increase in both the BC and CO₂ concentrations could be measured. The plumes could be properly separated by the TUG-PDA as marked by the integrated areas (A3). Afterwards, another vehicle passed by (V4). The emissions assigned to the fourth vehicle can be easily determined by the TUG-PDA and are also highlighted (A4). In this example, the emissions of the passing vehicles can be properly resolved. In contrast, 6 into the measured CO_2 plumes with and without interference from other vehicles/sources. Compared to Fig. 6, measured CO_2 plumes which were interfered are slightly higher compared to plumes without interference. This is due to the fact that most of the BC superimposed vehicle emissions are contained in the inference datasets. These are mainly vehicles with higher emissions, as BC peaks could be detected.
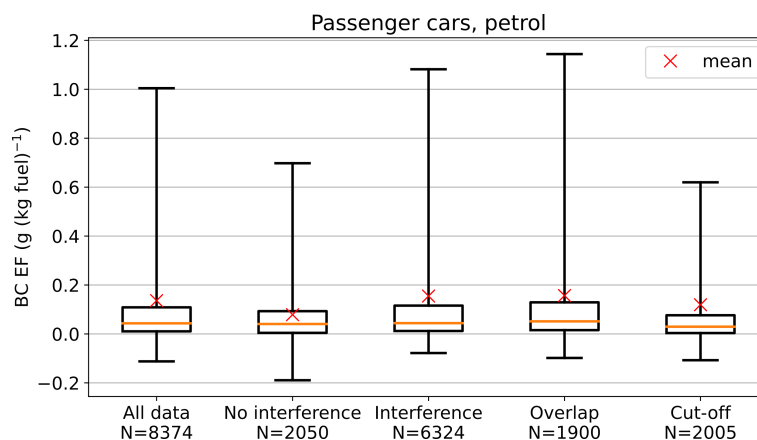
Figure C1. Influence of interference (CO_2 and BC) from other vehicles/sources on the BC emission distributions determined with the TUG-PDA. Measured EFs of petrol-powered passenger cars are used for comparison. Interference data includes both overlapping plumes and plume cut-offs (interference = overlap and/or cut-off).

Appendix D: Background conditions

Different measurement locations may be accompanied with varying environmental conditions such as wind or BG concentrations of the measured species. In Fig. 5b shows a data example where the emissions of most passing vehicles cannot be properly resolved. The first vehicle (V1) passes by, and small increase in CO₂ (and no BC emissions) can be seen. The exhaust plume is integrated by the TUG-PDA (A1). The plume of the second passing vehicle (V2) can also be properly detected (A2). During the integration of the emissions of V2, a third vehicle passes the PS site, but no change in COD1, 30-minute averaged BG concentrations for BC and CO₂ or BC concentrations is measured. Therefore, the TUG-PDA continues the processing of the exhaust plume for V2. For V3, no EF can be determined. Four seconds later, two vehicles (V4, V5) pass the PS spot with a gap of just one second. A significant are shown for three different measurement sites over a time period of 24 hours. At Location 1, rather stable BC concentrations can be noted along with a distinct increase in the CO_2 concentration is measured

~~after V4 passed by. After a small dip,~~ during the morning traffic period. In contrast, very high BC BG concentrations were measured at Location 4 on the presented measurement day accompanied by varying BG CO_2 values. Such different conditions depend on the season, meteorology, traffic density and other emission sources like industry and must be taken into account. High or varying BG concentrations can impact instrument performance. The BG concentration must be compensated for in the emission calculation and results can vary widely depending on the BG concentration used.
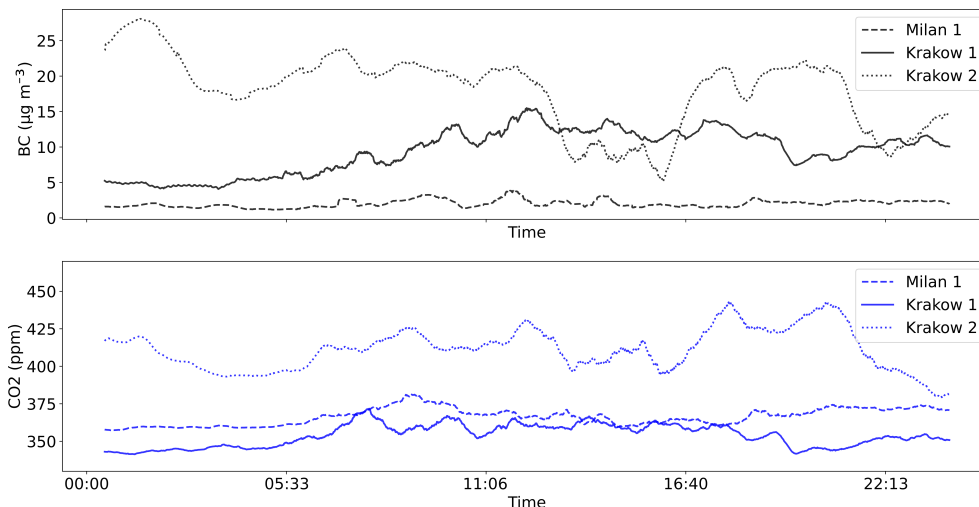
Figure D1. Background concentrations of BC (upper plot) and CO_2 (lower plot) from three different measurement sites. Concentrations are averaged with a half-hour running mean filter.

Appendix E: Influence of the sampling position on the captured plume strength

In Fig. E1, we compared the CO_2 concentrations when we measured either from the middle, the left, or the ~~CO~~right side of the road. All three sampling positions were used at least three times during the measurement campaigns. Distributions of mean CO_2 concentrations of the three sampling positions were calculated using the Monte Carlo method by drawing 500 samples of the measured CO_2 ~~concentration rises again, accompanied by a significant BC peak which are probably caused by V5. The emissions from the two vehicles are superimposed, and therefore cannot be certainly assigned to one of the two passing vehicles with such a short distance between them. Six seconds later, vehicle V6 is detected by the light barriers. A slight increase in both CO_2 and BC concentrations can be seen but the captured CO_2 peak is too small. After a short gap of nine seconds V7 is passing by.With a small delay of around 2 seconds, a strong CO_2 plume is measured along with a small BC peak. During the increase in both concentrations vehicle V8 passed the measurement point. EFs cannot be correctly determined for neither V7 or V8 due to the delay of the measured emissions from V7 and the short distance between the vehicles. Two seconds after V8, two vehicles (V9~~concentrations of passing vehicles from each measurement position 1,~~V10) pass by. An increase in CO_2 can be seen that is overlaid by~~ 000 times. Sampling from the middle of the road gives on average clearly higher signals as

compared to sampling from either side of the ~~previous emissions from V7. No EFs can be determined for V9 and V10 because~~ ~~of the small spacing between them. Mainly two criteria in the TUG-PDA are responsible if emissions cannot be properly separated. First, a minimum spacing of three seconds between the vehicles is specified for the TUG-PDA. If vehicles pass by with a spacing of less than three seconds, the emissions cannot be certainly attributed to one passing vehicle. Second, if the emission concentration is steadily rising over multiple vehicle passes the determined emission can not be correctly assigned to one vehicle.~~road, with a mean and σ of 654 ppm s and 1046 ppm s, respectively. Sampling from the left (mean: 480 ppm s, σ: 257 ppm s) delivers on average a higher signal as compared to sampling from the right side (mean: 455 ppm s, σ: 439 ppm s). A Gaussian distribution was assumed and fitted to the three datasets (Fig. E1).

~~Separable Not separable~~
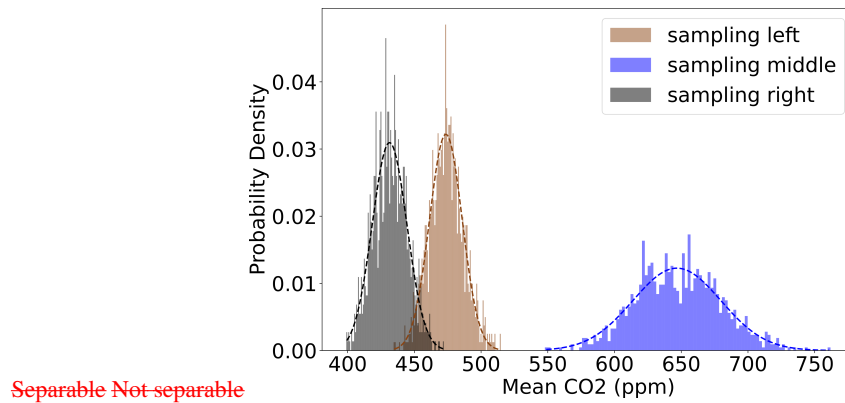
Figure E1. ~~Two PS time series examples (BC,~~ Distribution of mean CO_2 ~~) from captured plumes. The yellow, vertical, dashed lines mark the~~ ~~point~~ concentrations ~~of time when~~ the ~~vehicles passed the PS spot~~three sampling positions.~~**a)** Emissions can be separated for the individual vehicle passes. Four vehicle passes are shown where the assigned emissions are highlighted in different color schemes (A1 - A4). **b)** For most vehicle passes, the emissions for individual vehicle passes are not-separable. Ten vehicle passes are shown, of which emissions can be correctly determined for two.~~

Appendix F: Influence of weather conditions

Fig. ~~??~~11 and Fig. F2 show the influence of wind direction on the CR. We separated the directions in the 180° when the wind blows the plume towards the sampling point and in the 180° when the wind blows the plume away from the sampling point (Fig. F1).

The impacts of wind direction and speed on the capture rate at urban sampling locations are shown in Fig. F2. No real difference can be seen between winds blowing the exhaust towards or away from the sampling location. We assume that this is mainly due to differences between the measured local wind conditions at the sampling location and the measured data from the weather station nearby.
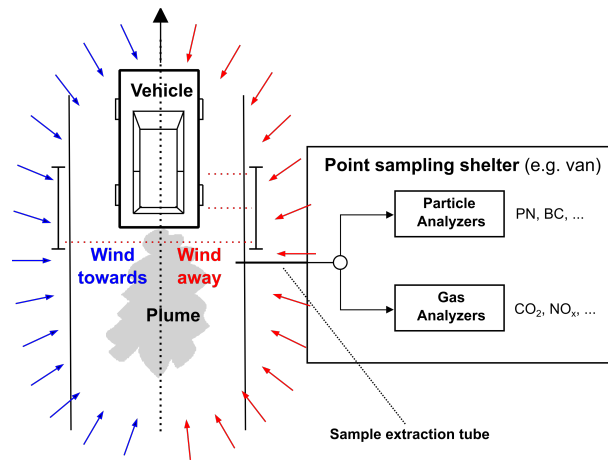
Figure F1. Schematic of the PS setup where the sampling is done from the roadside. The wind directions are indicated for winds which blow the exhaust plume toward or away from the sampling point.
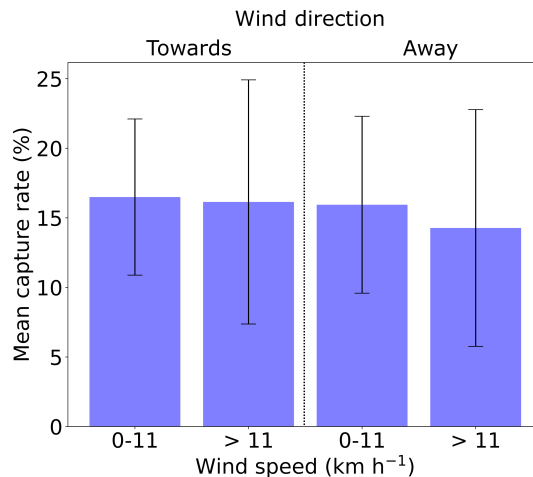

Figure F2. Influence of wind speed and direction in urban areas on the capture rate.

## Appendix G: Influence of misaligned measurement data

We emphasized the importance of compensating for sampling delays and the response times of instruments during the preprocessing steps of the data analysis. Additionally, the instrument responses are time-aligned to the vehicle passes which cause the fastest response of the measurement instruments (see Sect. 2.2.1). Misalignment has a major influence and impacts both the CR and the resulting ERs. Therefore, we investigate the effects resulting from misalignment between emission datasets from different instruments (e.g., CO_2 and pollutants) and between emission data and the vehicle pass times. First, we take a look at the latter. We deliberately misaligned the time series of the measurement equipment (e.g., CO_2, BC) as compared to the vehicle

pass times for time shifts (misalignment) between -5 and +5 s. Negative time shifts represent exhaust plumes that occur prior to the corresponding vehicle pass. A maximum CR is reached at a time shift of -1.5 s (Fig. G1a). There are several reasons why the CR peaks at slightly misaligned data. First, the TUG-PDA starts to scan the emission concentrations 1 s before the vehicle pass time (see Fig. 4). Second, the emission concentration time series datasets are time-aligned for plumes with the smallest time delay. These are plumes, e.g., of vehicles with the exhaust pipe located on the same side as the sampling position (if the sampling is performed from the side). Plumes of vehicles with an exhaust pipe on the other side are sampled with a slight delay (up to a few seconds). The negative time shift leads to additionally captured plumes in cases where the vehicles pass within small distance of each other. These additional records can be both correctly or wrongly assigned emissions, depending on the circumstances. For prior perfectly aligned plumes parts of the emissions are cut off because they are outside of the TUG-PDA start range leading to deviations in the resulting ERs. As the misalignment increases, the CR decreases steadily. The main reason is that the plumes from vehicles passing within short distances of one another can no longer be resolved. The substantial drop in time shifts below -3 s is caused by plumes peaking before the vehicles pass (e.g, see Fig. G5), and these peaks are not detected for larger negative time shifts. In addition to the influence on the CR, misalignment has a major influence on the resulting ERs. Fig. G1b shows the deviation of the calculated ERs caused by misalignment compared to the results calculated with the aligned datasets. The deviation increases as the misalignment increases, with median values ranging from -31.4 % to 0 % and between -162.1 % and 242.6 % on average. Fig. G2 shows the impact of misalignment between vehicle pass times and measured emission data on the integrated CO_2 concentration. The CO_2 concentration increases as the positive time shift increases and decreases as the negative time shift decreases. An increasing negative time shift in the time series causes the plumes to be cut off. Thus, BG concentrations that are too high are determined, which reduce the integrated concentrations (see e.g. Fig. G4). The deviations of the misaligned, integrated CO_2 concentrations from the properly aligned data are shown in Fig. G3.
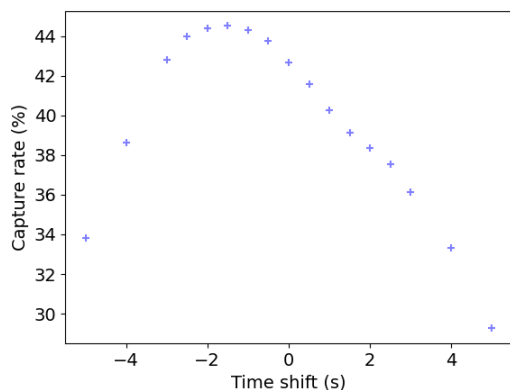
(a) Influence of misalignment on the capture rate.
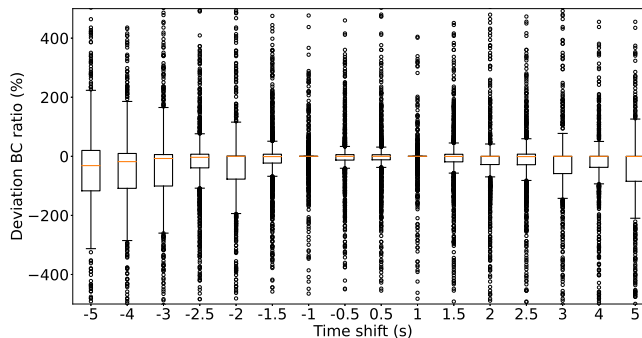
(b) The deviation of the resulting BC emission ratio due to the misalignment compared to the properly aligned data is shown.

Figure G1. Impact of improperly compensated sampling delay due to misalignment of time series data of the measurement equipment with the vehicle pass times.
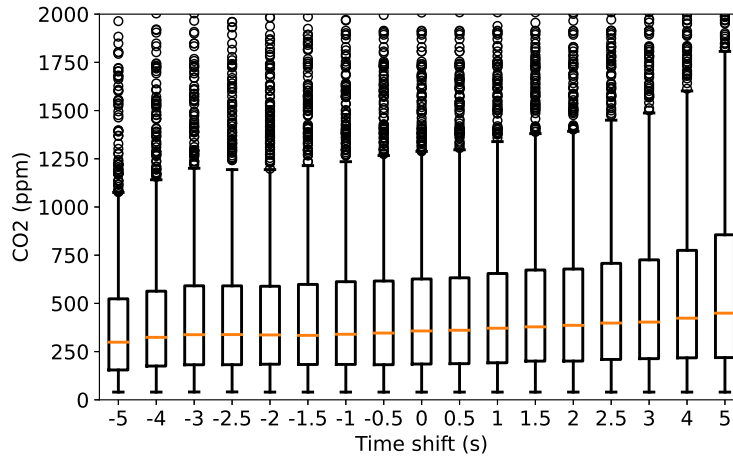
Figure G2. Impact of improperly compensated sampling delay on the integrated CO_2 concentration of the passing vehicles.
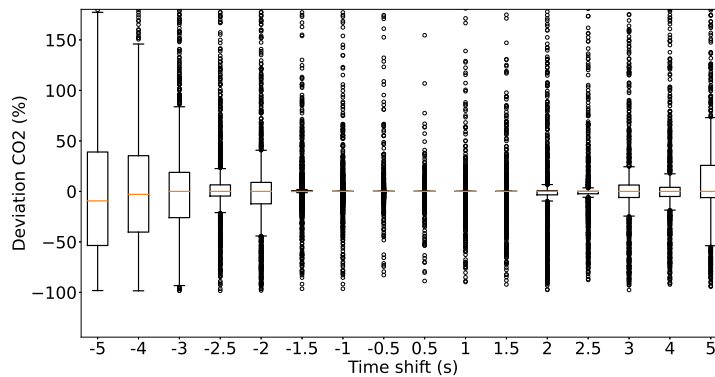

Figure G3. Impact of misalignment between measured emission concentrations and the vehicle pass times. Deviation of the properly aligned integrated CO_2 signal compared to the time shifted signal.

Two examples of misaligned instrument data related to the vehicle pass times are depicted in Fig. G4 and Fig. G5. The emission concentration time series from the instruments are 3 s time shifted (misaligned on purpose) compared to the vehicle pass times for both cases. In the graphs only the CO_2 concentration is shown. In both examples, the aligned data is shown in the same graph as the misaligned data. The TUG-PDA start range is shown on top, to illustrate the time range in which the TUG-PDA searches for an increasing concentration. The first case (Fig. G4) shows an example where the time shift can be compensated by the TUG-PDA. No other vehicle interferes with the measurement and the captured emissions are not too much delayed for proper detection. Only a small amount of the emissions are missed (highlighted in red). The second example (Fig. G5) shows one case where the emission concentrations are shifted to such an extent that they can no longer be associated

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with the vehicle pass. The positive slope of the plume is not covered by the TUG-PDA start range and therefore the entire plume is missed.
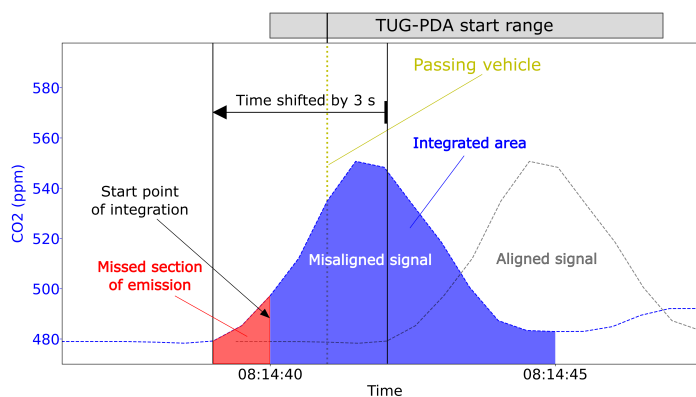
Figure G4. Time series example where the misalignment between instrument data (only CO_2) and vehicle pass times can be compensated by the TUG-PDA. The misaligned as well as the properly aligned time series are shown in the same plot.
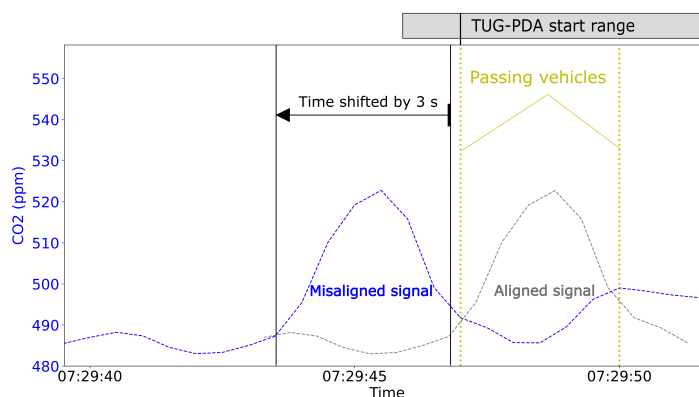

Figure G5. Time series example where the misalignment between instrument data (only CO_2) and vehicle pass times cannot be compensated by the TUG-PDA. The misaligned as well as the properly aligned time series are shown in the same plot. The TUG-PDA start range is shown for the first vehicle pass.

As a second step we analyzed the impact of misalignment between instrument data. In particular, CO_2 time series data must be properly aligned with respect to data from the measured pollutants (e.g., BC, PN, NO_x). We shifted the CO_2 time series in 0.5 s steps against the BC time series to investigate possible effects of misalignment on the results. Fig. G6 shows the deviation of the BC ratio as compared to the properly aligned data. As the positive time shift increases, there is a steady increase in the deviation. The deviation increases on average from -0.9 % for +0.5 s to -89.1 % for +5 s. A negative time shift has a different

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impact. Statistically, a small and slightly increasing impact is observed up to a time shift of -2.5 s, with a maximum median deviation of 6.4 %. From a time shift of -3 s and onward, the deviation increases significantly, with median values falling

980   between -64.5 % and -89.1 %. The small impact for time shifts between -2.5 and 0.5 s is mainly due to the peculiarities of the TUG-PDA. A small time shift between CO_2 and the pollutant is compensated, especially in the negative direction, because the datasets are processed individually. This effect is even more pronounced in the negative direction, because the data are time-aligned for vehicle plumes with the smallest time delay as already described above. The high deviations observed for small time shifts can mainly be referred to vehicle passages in a short period, where small misalignment errors have a strong

985   impact on the determined ERs.
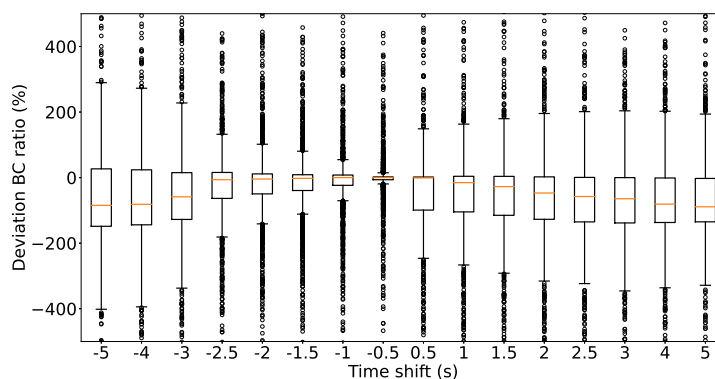
Figure G6. Impact of misalignment between CO_2 and BC instrumentation. The deviation caused by the misalignment of the resulting BC ER compared to the properly aligned data is shown.

In Fig. G7 and Fig. G8, two time series examples show possible effects of misalignment between the CO_2 and BC sensors. In these two cases, the CO_2 response is 3 s time shifted as compared to the BC response. In both examples, the original aligned data in the left graph is compared to the misaligned data in the right graph. In the first example (Fig. G7), the misalignment can be compensated by the TUG-PDA for two reasons. First, the emissions from the passing vehicle reach the sample inlet about

990   3 s after the vehicle has passed by. This could be the case because the tailpipe of the vehicle is located on the left-hand side and the sampling is conducted on the right-hand side, resulting in a transport delay. Second, the whole plume can be captured because there is no other vehicle present, which could cause an interfering plume. The second example (Fig. G8) shows one case where the time shift causes emissions to be assigned to the wrong vehicle. A substantial share of the CO_2 emissions of the second vehicle are wrongly assigned to the first vehicle. This results into a underestimated ER for the first vehicle.
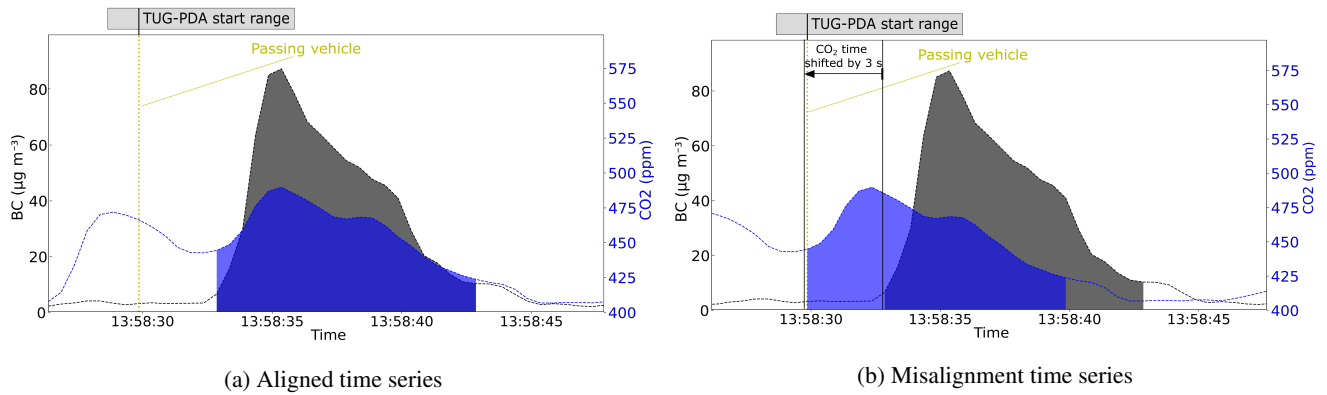
Figure G7. Time series example where the misalignment between CO_2 and BC sensors can be compensated by the TUG-PDA. Gray (BC) and blue (CO_2) shaded areas show the integrated areas.
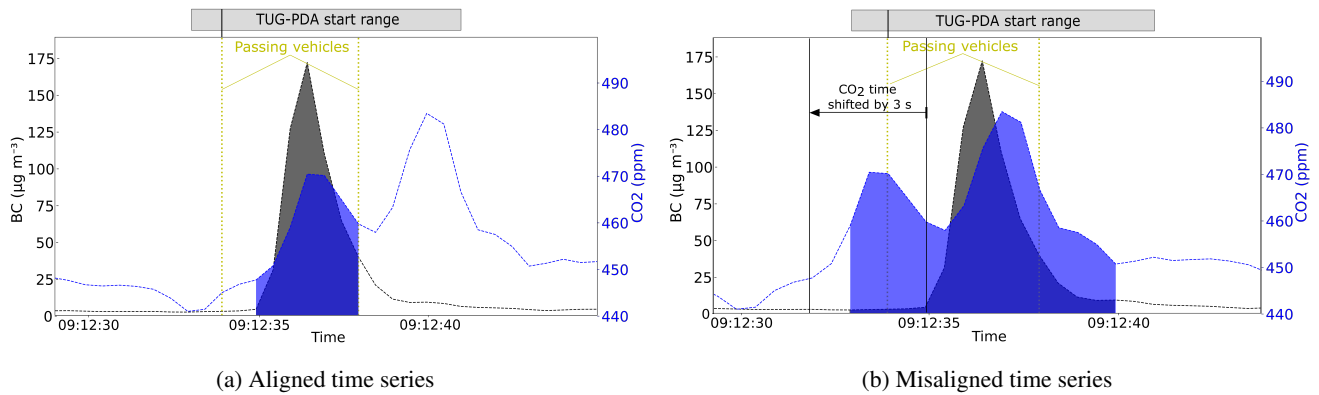

Figure G8. Time series example where the misalignment between CO_2 and BC sensors cannot be compensated. Gray (BC) and blue (CO_2) shaded areas show the integrated areas for the emission concentrations of the first passing vehicle. The TUG-PDA start range is shown for the first vehicle pass.

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