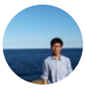
Remote sensing of on-road vehicle emissions: Mechanism, applications and a case study from Hong Kong

Article *in* Atmospheric Environment · March 2018

DOI: 10.1016/j.atmosenv.2018.03.035



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Atmospheric Environment 182 (2018) 58–74

Contents lists available at ScienceDirect

Atmospheric Environment

journal homepage: www.elsevier.com/locate/atmosenv

Review article

Remote sensing of on-road vehicle emissions: Mechanism, applications and a case study from Hong Kong

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ARTICLE INFO

Keywords:
Remote sensing
On-road vehicle emissions
High-emitter screening
Emission factors
Emission monitoring and control

ABSTRACT

Vehicle emissions are a major contributor to air pollution in cities and have serious health impacts to their inhabitants. On-road remote sensing is an effective and economic tool to monitor and control vehicle emissions. In this review, the mechanism, accuracy, advantages and limitations of remote sensing were introduced. Then the applications and major findings of remote sensing were critically reviewed. It was revealed that the emission distribution of on-road vehicles was highly skewed so that the dirtiest 10% vehicles accounted for over half of the total fleet emissions. Such findings highlighted the importance and effectiveness of using remote sensing for *in situ* identification of high-emitting vehicles for further inspection and maintenance programs. However, the accuracy and number of vehicles affected by screening programs were greatly dependent on the screening criteria. Remote sensing studies showed that the emissions of gasoline and diesel vehicles were significantly reduced in recent years, with the exception of NO_x emissions of diesel vehicles in spite of greatly tightened automotive emission regulations. Thirdly, the experience and issues of using remote sensing for identifying high-emitting vehicles in Hong Kong (where remote sensing is a legislative instrument for enforcement purposes) were reported. That was followed by the first time ever identification and discussion of the issue of frequent false detection of diesel high-emitters using remote sensing. Finally, the challenges and future research directions of on-road remote sensing were elaborated.

1. Introduction

The exposure to poor air quality continues to be a critical issue concerning the public health worldwide. The World Health Organization (WHO, accessed 25.05.2017a) analysed the small and fine particulate matter (PM_{10} and $PM_{2.5}$) data of 795 cities in 67 countries during 2008–2013, and concluded that global urban air pollution levels had increased by 8% despite improvements in some regions. Generally, the lowest urban air pollution levels are reported in high-income countries but the highest in low- and middle-income countries. It was reported that 92% of the world population was living in places where air pollution exceeded the WHO air quality guideline levels in 2014 and caused approximately three million premature deaths globally in 2012 (WHO, accessed 25.05.2017b). A variety of anthropogenic and biogenic sources contribute to the air pollution problem such as transportation, power plants, manufacturing industries, bushfires, volcanoes and sea spray (Atkins et al., 2010; Mohsen et al., 2018). Nowadays, on-road vehicle emissions are often believed to be the single largest contributor of atmospheric pollutants (Beaton et al., 1995; Franco et al., 2013; Pokharel et al., 2003; Ropkins et al., 2009). However, it can take a long time to clearly identify the real major source of air pollution. For example, in the case of Los Angeles area which suffered severe air pollution since the turn of the 20th century (Smith, 2013), where initially industrial sources were blamed, particularly oil refineries, chemical plants and power plants. The USA's first air pollution control district was established in Los Angeles in 1946 to address industrial pollution, but ignored automobile emissions (Van Vorst and George, 1997). Later Professor Haagen-Smit at the California Institute of Technology reported that the Los Angeles smog was caused by the complex photochemical reactions of organic compounds (mostly hydrocarbons from gasoline) and NO_x which were emitted by motor vehicles as well as the petroleum industry and solvent use (Haagen-Smit, 1962). Finally, the scientific community started to realise that automotive emissions were responsible for approximately half of the air pollution in the Los

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https://doi.org/10.1016/j.atmosenv.2018.03.035
Received 6 September 2017; Received in revised form 12 March 2018; Accepted 18 March 2018
Available online 19 March 2018
1352-2310/

Nomenclatures

AFR	Air/fuel ratio
EF	Emission factor
ETN	Emission Test Notice
FEAT	Fuel Efficiency Automobile Test
FTP	Federal Test Procedure
HKEPD	Hong Kong Environmental Protection Department
HKTET	Hong Kong Transient Emission Test
I/M	Inspection and maintenance
IR	Infrared
LPG	Liquefied petroleum gas
M_P	Molecular weight of pollutant P
NEDC	New European Driving Cycle
PEMS	Portable emissions measurement system
PM	Particulate matter
TWC	Three-way catalyst
UV	Ultraviolet
VSP	Vehicle specific power
Q_P	Concentration ratio of pollutant P over CO_2

Angeles area (Van Vorst and George, 1997).

Great efforts have been made to reduce vehicle exhaust emissions and to meet increasingly stringent air quality standards. Fig. 1 shows the Euro 1–6 emission standards for diesel passenger cars. The emission regulations have been tightened greatly during the past two and half decades. For example, the NO_x emission limit of diesel passenger cars was 0.50 g/km in the Euro 3 standards (European Parliament and Council, 1998), which was reduced to 0.08 g/km in the Euro 6 standards (European Commission, 2012). However, the expected reduction in NO_2 concentration at road sites was not observed with more stringent vehicle emission standards (Carslaw et al., 2011). Recent studies showed that NO_x emissions of diesel cars under real-world conditions changed little or even increased for post Euro 3 stages (Carslaw et al., 2011; Carslaw and Rhys-Tyler, 2013; Chen and Borken-Kleefeld, 2014; Pujadas et al., 2017). This occurred because these emission standards were implemented in predefined laboratory testing cycles using chassis or engine dynamometers, such the New European Driving Cycle (NEDC) and Federal Test Procedure (FTP) which did not reflect real-world driving conditions (and hence emissions) accurately. In addition, testing was conducted on new or well-maintained engines/vehicles which ignored the effect of deterioration of engine and after-treatment systems on vehicle performance (Ropkins et al., 2009). Moreover, automotive manufacturers may only optimise vehicle fuel economy and emissions within these homologation cycles to obtain the certification to enter a specific market. Therefore, a number of techniques have been developed to measure vehicle emissions under real-world driving conditions in recent years, such as on-road remote sensing, exhaust plume chasing, portable emissions measurement system (PEMS), tunnel and roadside ambient measurements (Borken-Kleefeld, 2013; Franco et al., 2013; Ropkins et al., 2009). Although they may be less accurate or repeatable than laboratory testing, real-world emission measurements play an important role in identifying the gap between laboratory and real-world emissions, and in controlling automotive emissions.

Table 1 compares the mechanism, advantages and disadvantages of different on-road emission measurement techniques. PEMS directly measures the absolute emissions of the target vehicles by carrying a set of emission measurement instruments on-board (Rašić et al., 2017), with the highest accuracy compared with other on-road measurement techniques. Similarly, plume chasing measures the emissions of the target vehicle, but with the measurement instruments installed on a laboratory vehicle or trailer that follows the vehicle being tested (Lau et al., 2015). The main advantage of PEMS and plume chasing is that they can measure a long series of emission data under a wide range of real-world driving conditions, including some that would be difficult to replicate in laboratory (e.g. large road gradients and large heavy-duty vehicles). However, PEMS and plume chasing measurements are expensive and cannot be used for large numbers of vehicles. Additionally, the extra heavy weight of PEMS may bias the measurements (especially for light vehicles) and the accuracy of plume chasing is significantly reduced. On the other hand, tunnel and ambient measurements offer the ability to measure emissions of a large number of vehicles. Tunnel technique measures the ambient pollutant concentrations at the tunnel entrance and exit (Smit et al., 2017). Emission factors (EFs) are calculated from the concentration difference, combined with tunnel features (e.g. tunnel length, cross area), traffic conditions and wind. Ambient technique measures the ambient pollutant concentrations at urban roadside sites (Ke et al., 2013). However, tunnel and ambient techniques cannot determine the emissions of specific vehicle classes or individual vehicles due to the nature of indirect measurements. Moreover, non-exhaust emissions are also measured with vehicle emissions with tunnel and ambient techniques. On-road remote sensing combines the advantages of the aforementioned four techniques, which can measure the emissions of typically thousands of vehicles daily and resolve the emissions for both individual vehicles and specific vehicle classes. Moreover, remote sensing is the most economic technique among them on a cost per vehicle basis (Burgard et al., 2006a). These advantages make remote sensing an ideal tool for a variety of applications, such as monitoring real-world fleet emissions, identifying high-emitting vehicles for inspection and maintenance (I/M) programs, and assessing the effectiveness of emission control programs and technologies.

On-road remote sensing technique was developed in the Fuel Efficiency Automobile Test (FEAT) program by the University of Denver in the late 1980s (Stedman and Bishop, 1990). It measures the concentration ratios of pollutants over CO_2 in the exhaust plume of a passing vehicle. Remote sensing initially only measured the CO ratio (Bishop et al., 1989; Stedman, 1989), which aimed to identify the rich-burning (high CO) vehicles and then tune or repair them to more stoichiometric (more efficient) vehicles. The measurement capacities of HC (Zhang et al., 1993), NO (Bishop and Stedman, 1996; Popp et al., 1999a), PM (represented by particle opacity) (Stedman and Bishop, 2002), and NO_2, SO_2 and NH_3 (Burgard et al., 2006d) were developed soon after. Remote sensing can measure instantaneous emission ratios

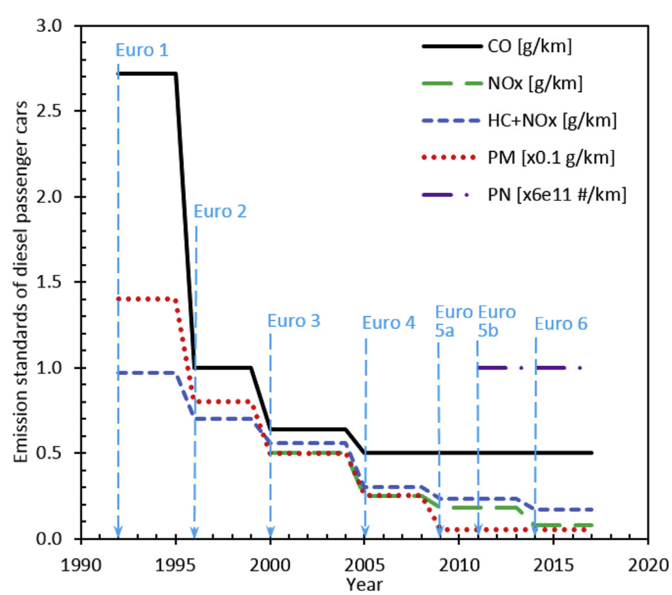

Fig. 1. Trajectories of the European emission standards for diesel passenger cars.

Table 1
Comparison of vehicle emission measurement techniques under real-world driving conditions.

Technique	Method	Advantage	Disadvantage
PEMS	Measures target vehicle emissions by carrying measurement instruments on-board	High accuracy Emission data of a journey Individual vehicles & vehicle classes	Small sample size Extra weight of PEMS may bias the measurements, especially for light vehicles
Plume chasing	Measures target vehicle emissions by a following laboratory vehicle carrying measurement instruments	Emission data of a journey Individual vehicles & vehicle classes	Small sample size Limited speed and minimum distance for safety
Tunnel measurement	Measures pollutant concentrations at tunnel's entrance and exit	Large sample size Well-defined wind	Difficult to determine emissions of specific vehicle classes or individual vehicles Limited driving conditions (steady speed) Induced wind by large vehicles Non-exhaust emissions (e.g., tyre and brake wear)
Ambient measurement	Measures ambient pollutant concentrations at roadside	Large sample size	Difficult to determine emissions of specific vehicle classes or individual vehicles Non-exhaust emissions (e.g., household and industry) Indirect measurements
Remote sensing	Measures vehicle emissions when passing through IR and UV beams on-road	Large sample size Individual vehicles & vehicle classes Cheapest on per vehicle basis	Only measures ratios of pollutants over CO_2 Emission data measured in half a second Limitations in site selection (positive road grade, single lane and free flowing traffic)

of thousands of vehicles per day under real-world conditions without interference to driving. It has attracted great attention since its development and has been used in a variety of applications worldwide (Zhang et al., 1995). On-road remote sensing is considered an effective, economical and socially acceptable tool for use in automobile emission control.

The aim of this article is to critically review the published studies on remote sensing of on-road vehicle emissions. Firstly, the mechanism, accuracy, advantages and limitations of remote sensing technique are introduced. Then the applications and major findings of remote sensing are examined. Thirdly, the experience and issues of using remote sensing for identifying the on-road high-emitters in Hong Kong (as an enforcement tool) are reported. To the best of the authors' knowledge, it is the first paper that evaluates the problems associated with using remote sensing in screening high-emitting diesel vehicles. Finally, the challenges and future research directions of on-road remote sensing are elaborated.

2. On-road remote sensing

2.1. Operating mechanism

On-road remote sensing of vehicle emissions is an application of absorption spectroscopy (Burgard et al., 2006a). As shown in Fig. 2, an on-road remote sensing system consists of infrared (IR) and ultraviolet (UV) beam sources and detectors, speed and acceleration sensors and a vehicle plate camera. The system is triggered by the beam being blocked by a vehicle. The camera captures an image of the vehicle number plate which provides registration information of the passing vehicle, including the maker, manufacture year, engine size, fuel type, exhaust after-treatment technology and emission standards. The speed and acceleration of the passing vehicle are also measured. Each emission species has a series of absorption bands in the IR or UV regions. The IR and UV detectors measure the attenuation of a specific wavelength for each emission when the beam passes through the exhaust plume. Table 2 lists the beam wavelengths used for the emissions measured in remote sensing. One emission species has several absorption peaks in the IR or UV spectrum, and thus different wavelengths may be used in different devices or studies for the same emission. For example, a wavelength of 4.6 µm was used for CO measurement in early studies (Bishop et al., 1989; Burgard et al., 2006a) but was changed to 3.6 µm in recent studies (Bishop et al., 2012a, 2016). As shown in Table 2, CO, CO_2 and HC emissions are measured in the IR region and NO, NO_2, SO_2 and NH_3 emissions are measured in the UV region. PM opacity is measured in both IR and UV regions. Although remote sensing has the capacity to measure a wide range of emissions in the vehicle exhaust, the most often measured and reported emissions are CO, HC and NO because other emissions are either too low (e.g. SO_2 and NH_3) (Bishop and Stedman, 2015a; Burgard et al., 2006c) or not reliable (e.g. PM) (Lau et al., 2015; Moosmüller et al., 2003; Stedman and Bishop, 2002). Once the remote sensing system is triggered, it typically records the data at a frequency of 100 Hz (although a 200 Hz sampling frequency was used at General Motors R&D Centre (Cadle and Stephens, 1994)) and lasts for a half second. The system compares the beam intensity of each pollutant with the reference signal and that before the vehicle arrives. By doing so, remote sensing records 50 independent readings of the beam intensity change signals (in voltage) for each

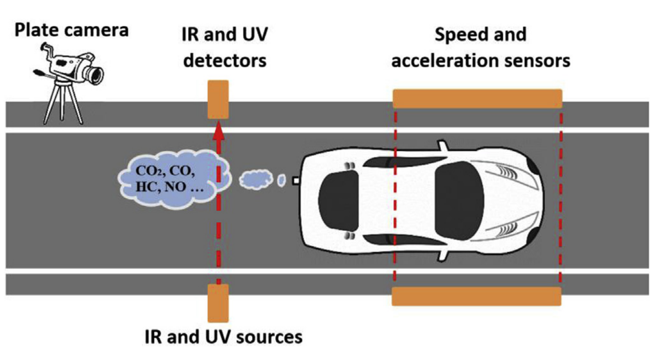

Fig. 2. Schematic of the on-road remote sensing system.

Table 2
Wavelengths of the IR and UV beams used in remote sensing.

Pollutant	IR and UV beam wavelength	Reference
Reference	3.9 µm	(Burgard et al., 2006a)
CO	4.6 µm	(Burgard et al., 2006a)
CO_2	4.3 µm	(Burgard et al., 2006a)
HC (propane)	3.4 µm	(Burgard et al., 2006a)
NO	227 nm	(Zhang et al., 1996a)
NO_2	438 nm	(Burgard et al., 2006d)
SO_2	219, 221 and 222 nm	(Burgard et al., 2006d)
NH_3	209, 213 and 217 nm	(Burgard et al., 2006d)
PM (opacity)	3.9 µm and 240 nm	(Stedman and Bishop, 2002)

pollutant. Then, the computer plots ΔCO, ΔHC, ΔNO, $ΔNO_2$, $ΔSO_2$, $ΔNH_3$ and ΔPM versus $ΔCO_2$, where Δ indicates the difference of each pollutant's signals in the plume and in the ambient air ($\Delta P = P_{plume} - P_{ambient}$). The least square slopes of these lines are the CO/CO_2, HC/CO_2, NO/CO_2, NO_2/CO_2, SO_2/CO_2, NH_3/CO_2 and PM/CO_2 ratios (indicated by Q_P thereafter). For a given exhaust plume, these concentration ratios are constant (Bishop et al., 1989; Burgard et al., 2006a). Since the effective plume path length and the amount of plume measured are influenced by a number of factors such as wind, turbulence, engine size and exhaust pipe height, the system can only determine the relative concentration ratios of pollutants over CO_2.

These relative concentration ratios are very useful parameters to evaluate the engine's combustion system. The air/fuel ratio (AFR), absolute emission concentrations and EFs can be derived from the remote sensing data. Equation (1) is the combustion formula of a typical hydrocarbon fuel:

$$CH_2 + a\,(0.21O_2 + 0.79N_2) \rightarrow b\ N_2 + c\ CO_2 + d\ H_2O + e\ O_2 + f\ CO + g\ C_3H_8 + h\ NO \quad (1)$$

The absolute emission concentrations can be calculated based on the following assumptions. Firstly, chemical formula CH_2 is assumed for gasoline and diesel fuels, and $(0.21O_2 + 0.79N_2)$ for air. The assumption of CH_2 for all hydrocarbon fuels is a very useful approximation (Burgard et al., 2006a). In some studies, different formulas may be used, such as $CH_{1.85}$ (Chan and Ning, 2005). However the difference caused by this would be minor (e.g., only 4% for AFR calculation (Stedman and Bishop, 1990)) because the majority of mass is still in the carbon even for fuels with very different formulas (e.g., CH_4) (Burgard et al., 2006a). Secondly, the engine is running rich with no excess oxygen in the exhaust ($e = 0$). This is true for the conventional gasoline engines which are always operated around stoichiometric AFR and a rich mixture is used in cold start, high-load or acceleration conditions. However, diesel engines have no throttle and are always operated under lean conditions. Even at full load, the mass of fuel injected is only about 5% of the mass of air in the cylinder (equivalent to ~20 of AFR) (Heywood, 1988). However, the stoichiometric AFR is about 14.5 for diesel fuel. CO and HC are generated in the diffusion flame in diesel engines although the overall AFR is relatively lean. Finally, the calculations are performed on a dry basis and assume an 8-cm path length (Bishop, 2014). By applying the principles of carbon, hydrogen and oxygen balance, the AFR and absolute percentages of CO_2, CO, HC and NO emissions can be calculated as follows (Bishop, 2014):

$$AFR = \frac{4.93 \times (3 + 2Q_{CO} + Q_{NO})}{1 + Q_{CO} + 3 \times 2 \times Q_{HC}} \quad (2)$$

$$CO_2 = \frac{42}{2.79 + 2Q_{CO} + 0.84Q_{HC} + Q_{NO}}[\%] \quad (3)$$

$$CO = Q_{CO} \times CO_2[\%] \quad (4)$$

$$HC = Q_{HC} \times CO_2[\%] \quad (5)$$

$$NO = Q_{NO} \times CO_2[\%] \quad (6)$$

The AFR calculation will be corrected according to equation (7) if the water-gas shift reaction ($CO + H_2O \rightleftharpoons H_2 + CO_2$) is considered (Burgard et al., 2006a):

$$AFR = \frac{4.93 \times (10.5 + 9Q_{CO} + Q_{CO}^2)}{(3.5 + Q_{CO})(1 + Q_{CO} + 3 \times 2 \times Q_{HC})} \quad (7)$$

Two multipliers (3 and 2) are used in equations (2) and (7) because HC is measured as propane (C_3H_8) in remote sensing (hence a multiplier of 3), while multiplier 2 is the conversion factor from non-dispersive infrared (NDIR) to flame ionization detector (FID) due to different sensitivities of the two HC measurement techniques (Burgard et al., 2006a). The NDIR to FID conversion factor varies from 2.0 ± 0.1 to 2.2 ± 0.1 (Singer et al., 1998). Thus different conversion factors may be used in different studies, e.g. 2.2 in Pokharel et al. (2002) and 1/0.493 in Chan and Ning (2005); Li et al. (2016). Some early studies did not apply this conversion factor (Bishop and Stedman, 1996; Singer and Harley, 1996; Stedman et al., 1994). In early studies, the absolute emission concentrations were calculated from the concentration ratios (Beaton et al., 1995; Bishop et al., 1989; Bishop and Stedman, 1996; Popp et al., 1999a; Zhang et al., 1993). The remote sensing devices also present the measured emissions in percentages. However, this was considered a mistake because the measurement of N relative concentration ratios was not enough to calculate N+1 absolute emission concentrations and the CO_2 percentage had no meaning except as a denominator (Burgard et al., 2006a). Therefore, a back-calculation to the original concentration ratios or converting them to EFs was recommended (Burgard et al., 2006a), which removed the assumptions for calculating the absolute concentrations. By applying only the principle of carbon balance, the mole number and EF in [g/kg fuel] of pollutant P can be calculated by equations (8) and (9) (Bishop and Stedman, 2013):

$$\frac{moles\ \ P}{moles\ \ C} = \frac{P}{CO_2 + CO + 3HC} = \frac{Q_P}{1 + Q_{CO} + 3 \times 2 \times Q_{HC}} \quad (8)$$

$$EF_P = \frac{M_P}{M_{fuel}} \times \frac{Q_P}{1 + Q_{CO} + 6Q_{HC}}[g/kg\ \ fuel] \quad (9)$$

where M_P is the molecular weight of pollutant P in g/mol and M_{fuel} is 0.014 kg/mol for CH_2. Therefore, the fuel mass based EFs of CO, HC and NO can be calculated by equations 10–12:

$$EF_{CO} = \frac{28}{0.014} \times \frac{Q_P}{1 + Q_{CO} + 6Q_{HC}}[g/kg\ \ fuel] \quad (10)$$

$$EF_{HC} = \frac{2 \times 44}{0.014} \times \frac{Q_P}{1 + Q_{CO} + 6Q_{HC}}[g/kg\ \ fuel] \quad (11)$$

$$EF_{NO} = \frac{30}{0.014} \times \frac{Q_P}{1 + Q_{CO} + 6Q_{HC}}[g/kg\ \ fuel] \quad (12)$$

The fuel volume based EFs (g/L fuel) can be calculated if the fuel densities are known, e.g. 0.85 kg/L for diesel fuel (Chan and Ning, 2005) and 0.74 kg/L for gasoline fuel (Guo et al., 2007b). The distance based EFs (g/km) can also be calculated if the fuel economy (FE) factors are known for each vehicle type. For example, FE factors of 2.0 L/100 km for light-duty motorcycles (engine size ≤ 50 cc), 2.8 L/100 km for heavy-duty motorcycles (engine size > 50 cc) and 8.5 L/100 km for light-duty gasoline vehicles were used for the vehicles in Macao (Zhou et al., 2014). The overall EF for the whole fleet can be estimated by taking into account the fraction of each vehicle class. The emission inventory of the whole fleet can be obtained by multiplying the overall EF with the total fuel consumed by that fleet.

2.2. System set-up

Fig. 2 shows a typical arrangement of on-road remote sensing system, although other arrangements are also possible. Alternatively, the beam sources and detectors are placed together and a mirror is placed on the other side of the road to reflect the beam from the source to detector (Chan and Ning, 2005; Ko and Cho, 2006). An angled source-mirror-detector arrangement was used in a tunnel environment with a dual-lane and elevated road shoulder (Bishop et al., 1994). Recently, a down-facing configuration remote sensing system (EDAR) was developed (Ropkins et al., 2017), which could be used in multi-lane traffic. The IR and UV beams are usually placed 10 inches above the road which is the average height of exhaust pipe for most light-duty vehicles. Raised platforms are needed for the beam sources and detectors to measure the emissions of top-arranged exhaust pipes of heavy-duty diesel vehicles or buses (Bishop et al., 2001b; Burgard and Provinsal, 2009). Both laboratory and regular field calibrations (typically every 2 h) using known gas concentrations are required to ensure measurement quality for each remote sensing study. The site condition determines driving conditions and thus emission characteristics. The selection of site is of primary importance for remote sensing measurements (Cadle and Stephens, 1994). A proper measurement site should meet the following requirements (Bishop and Stedman, 1996, 2008; Borken-Kleefeld, 2013; Cadle and Stephens, 1994).

1) The site is safe for the drivers, operators and remote sensing devices.
2) Single lane traffic (or multi-lane that could be directed to single lane) with enough shoulder space is preferred.
3) The optical path length should be no longer than 13 m to avoid decreased sensitivity and increased background noise for non-dispersive IR and UV techniques. The optical path length could be extended to 88 m for the tunable infrared laser differential absorption spectroscopy technique (TILDAS) (Jimenez et al., 2000).
4) A sufficient number of vehicles should be observed at the measuring site.
5) Free flowing traffic is preferred and a steady acceleration is optimal.
6) The engine should be under load to provide enough exhaust plume. Therefore a positive acceleration or small road gradient is desirable.
7) Dry weather and a clean environment are preferred. Ambient temperature and humidity do not affect the measurements. However, rain droplets, snowflakes and dust will cause measurement noise and may result in invalid measurements.
8) The measurements are usually performed in day time for capturing the images of vehicle plates. However, remote sensing also works well at night time.

Additional selection criteria should be taken into consideration for different study purposes. For screening of high-emitting vehicles, the site should be several minutes away from where vehicles commence a trip from cold-start to avoid false detection. Off-cycle high-load or high-emission events should be avoided as well, e.g. steep hills. For EF and model development purposes, several sites covering different driving conditions and vehicle types are needed. For a long-term inspection program, no prospect for site construction in the foreseeable future is required.

2.3. Accuracy

Table 3 compares the accuracy specifications of three typical emission testing devices, including an AccuScan™ RSD5000 remote sensing device, a Horiba OBS 2200 PEMS and Signal Instruments laboratory gas analysers. As shown in Table 3, the uncertainties of remote sensing are relatively large compared with those of laboratory testing and PEMS. The accuracy of remote sensing depends on the device and also the setup of the system (e.g. alignment of beam path). Other system accuracies have also been reported. For example, uncertainties of ± 5% for CO, ± 15% for HC and ± 15% for NO were frequently reported for the University of Denver's FEAT devices (Bishop and Stedman, 1996, 2008). Small negative values may be recorded due to the measurement noise and inaccurate determination of the background concentration (ESP and McClintock, 2007). They may appear more frequently for modern and very clean vehicles. It should be noted that these negative values have to be included and not rounded to zero (Bishop and Stedman, 2015a; Borken-Kleefeld, 2013).

2.4. Advantages and limitations

The major advantage of remote sensing is its ability to rapidly measure a large number of vehicles under real-world driving conditions at a relatively low cost. Remote sensing can measure the emissions of a vehicle in less than 1 s and a time interval of 4 s between two vehicles will not have significant interference on the measurements (Cadle and Stephens, 1994). Typically, about 70–80% of the measured data are valid after eliminating the invalid gas measurements, and unreadable and out-of-date plates (Bishop and Stedman, 2008). Therefore thousands of valid measurements can be taken at one site per day. Moreover, the cost of remote sensing is minimal (less than 0.5 dollar per test (Bishop and Stedman, 1996; Stedman and Bishop, 1990)), making it the most economic emission testing method on a cost per vehicle basis (Burgard et al., 2006a). In addition, the measured emission data is resolved for both individual vehicles and specific vehicle classes. However, the following limitations of remote sensing need to be considered.

1) A key assumption for Q_{CO} measurement is that the engine is running with a rich AFR and the emission control system is not fully operational (Bishop and Stedman, 1996; Burgard et al., 2006a). This is true for the conventional gasoline engines, but not for diesel and modern gasoline direct-injection stratified-charge vehicles which employ lean combustion technology. Since remote sensing cannot distinguish the excess oxygen in the exhaust from the large amount of oxygen in the atmosphere (Burgard et al., 2006a), the AFR cannot be calculated from Q_{CO} and Q_{HC} ratios and the errors of the calculated emission concentrations may be large for a vehicle running under lean conditions.
2) Remote sensing only measures a vehicle's emissions in less than 1 s under one engine condition. With a large sample size, remote sensing can provide accurate results on fleet average emissions. However, when it comes to an individual vehicle, it may be

Table 3
Typical accuracy specifications of remote sensing (RSD5000, 2017), PEMS (Horiba, 2017) and laboratory emission testing (Signal Instruments, 2018).

Parameter	Remote sensing (AccuScan RSD5000) [a]	PEMS (Horiba OBS 2200) [a]	Laboratory emission testing (Signal Instruments 7000FM, 3000HM and 4000VM) [a]
$\frac{CO\,(\%)}{CO_2\,(\%)}$	± 0.015 or ± 5% of reading [b] ± 0.007 or ± 10% of reading [c]	–	–
$\frac{HC\,(ppm)}{CO_2\,(\%)}$	± 10 or ± 15% of reading [b] ± 6.6 or ± 10% of reading [c]	–	–
$\frac{NO\,(ppm)}{CO_2\,(\%)}$	± 10 or ± 15% of reading [b] ± 10 or ± 10% of reading [c]	–	–
CO (%)	± 0.15 or ± 15% of reading [b] ± 0.1 or ± 10% of reading [c]	± 0.3% of range or 2.0% of reading	± 0.00002 or ± 1% of range
HC (ppm)	± 150 or ± 15% of reading [b] ± 100 or ± 10% of reading [c]	± 0.3% of range or 2.0% of reading	± 0.2 or ± 1% of range
NO (ppm)	± 225 or ± 15% of reading [b] ± 150 or ± 10% of reading [c]	± 0.3% of range or 2.0% of reading	± 0.2 or ± 1% of range
Speed	± 1.6 km/h (8.0–112.7 km/h)	–	–
Acceleration	± 0.8 km/h/s (8.0–112.7 km/h)	–	–

[a] Whichever is larger.
[b] For CO_2 plume < 20%-cm.
[c] For CO_2 plume > 20%-cm.

insufficient to accurately characterize a vehicle's emission performance with just a single instantaneous pass-by measurement. Even normally functioning engines may have emission spikes. For the purposes of high-emitter or clean-vehicle screening, extra information and filters are required to increase the confidence in the assessment of individual vehicle's emissions and thus to decrease false detections.
3) The uncertainties of remote sensing are relatively large compared with laboratory emission testing and PEMS.
4) Remote sensing measurements can be only taken in traffic with a single lane (possible in dual-lane traffic but not preferred) and in dry weather with a clean environment.

3. Applications and main findings

3.1. Identification of high-emitters

Zhang et al. (1994) reported that the distribution of on-road vehicle emissions was highly skewed. Remote sensing studies showed that the dirtiest 7% vehicles produced 50% of CO, 10% vehicles produced 50% of HC and 10% vehicles produced 46% of NO, while the cleanest 60% vehicles generated negligible emissions (Beaton et al., 1995; Popp et al., 1999a). Such skewed distribution applies for both old and new vehicles. It was reported that 20% of the highest emitting of the newest vehicles were worse than 40% of the lowest emitting vehicles from any model year, even including vehicles manufactured before the introduction of catalytic converters in the 1970s (Beaton et al., 1995). If these few dirty vehicles can be identified and certain measures are taken (e.g. maintenance, toll, tax), the automobile emissions can be reduced significantly. Remote sensing can measure the instantaneous emissions of a large number of vehicles under real driving conditions at a relatively low cost, making it an ideal tool for identifying both high-emitting and clean vehicles. The former application is aimed to detect dirty vehicles for the I/M programs, while the later one is to exempt clean vehicles from the mandatory periodic inspections, reducing inconvenience and cost for both vehicle owners and governmental regulators.

Remote sensing was primarily developed for detecting high-emitting vehicles (Cadle and Stephens, 1994), although very limited studies have been reported in this area. In addition, most of such studies were carried out in the USA (Table 4). Early studies (1997 and earlier) mainly relied on CO measurement and were aimed to evaluate the effectiveness and accuracy of remote sensing.

Rueff (1992) selected eight CO and two HC gasoline high-emitters by remote sensing for a Test-and-Repair program. It was found that CO and HC emissions were reduced by 73% and 80% after major emission system repairs, indicating that remote sensing was a cost-effective technique ($229/t) for reducing fleet wide CO emissions. However, the HC high-emitters identified by remote sensing did not show high HC emissions in the FTP testing. Bishop et al. (1993) identified 114 high-emitters from 17422 measurements and offered them a free repair. A 50% reduction in CO was observed after repairs and the estimated cost effectiveness was only $200/t. A Smart Sign program was performed in Denver between 1996 and 1997 to notify the drivers the emission performance of their vehicles when they passed by a remote sensing site (Bishop et al., 2000). The results showed that fleet emissions were dominated by the FAIR and POOR vehicles, while 86.7% vehicles were GOOD which only contributed to 23.8% of the total fleet emissions. This program was estimated to produce more than 4000 voluntary repairs in that year and the cost was only about $0.02/test. The California and Michigan study (Stephens et al., 1997) reported that the high-emitter frequency within any model year had no obvious relation to that model year's certification standards and the frequency increased with the increase of vehicle age.

Regarding the accuracy of remote sensing, Beaton et al. (1995) and Bishop and Stedman (1996) identified 3271 high-emitters from 60487 measurements in a 10-day operation and 307 of the high-emitters were randomly chosen to take an immediate roadside inspection. They found that only 8% of the high-emitters were false detections. Stephens et al. (1996) analysed the second-by-second emission data from the FTP driving cycle. The results showed that properly functioning vehicles exceeded the cutpoints by only 0.03%, 0.05% and 0.01% of the FTP cycle time for CO, HC and NO respectively, indicating that remote sensing was effective in isolating the high CO and HC emitting vehicles.

Such early studies have shown the effectiveness and low-cost of using remote sensing for screening high-emitting vehicles, although they have the following main limitations:

1) A fixed conservative criterion was often used for all the high-emitting vehicles e.g. CO > 4% (Rueff, 1992; Stephens et al., 1996, 1997).
2) The number of vehicles used for screening verification was relatively small (ranging from 10 (Rueff, 1992) to 307 (Beaton et al., 1995; Bishop and Stedman, 1996)).
3) The vehicles used for verification were mostly light-duty gasoline vehicles.

The post-1997 studies included HC, NO and PM measurements and investigated the effect of cutpoints on the identification of high-emitting vehicles, such as the combination of multiple cutpoints or multiple remote sensing readings (hits) above the cutpoints as the screening criteria.

The 1997–1998 Denver study (McClintock, 1999) used cutpoints based on CO, HC or a combination of CO and HC. It was reported that a significant number of high-emitting vehicles identified by remote sensing passed the subsequent IM240 test and using two hits of cutpoints did not significantly increase the screening accuracy. However the IM240 tests were conducted several months after the remote sensing measurements, which might have caused the significant difference. The 2000 California study (BAR, 2001) measured the emissions of 306 high-emitters identified by remote sensing in an Acceleration Simulation Mode (ASM) pull-over test. An identification accuracy of 83–88% could be achieved by applying cutpoints of 2% CO or 1000 ppm HC or 1500 ppm NO. The accuracy could be increased to 92% if applying multiple remote sensing readings exceeding the cutpoints. Moreover optimal cutpoints could be determined for more specific model year groups. The 2007 Michigan study (ESP and McClintock, 2007) combined CO, HC, NO or UV smoke factor as the high-emitter criteria. A vehicle would be identified as a high-emitter if it exceeded one of the four cutpoints. The results showed that 10% high-emitters of one pollutant were also high emitters of at least another pollutant and diesel vehicles had higher rates of smoke and NO high-emitters than gasoline vehicles. However, no verification by roadside or laboratory testing was conducted. Pujadas et al. (2017) used the 95th percentile of the respective emission ratios as the high-emitter cutpoints for both gasoline and diesel vehicles. The results showed that most gasoline high-emitters were Pre-Euro vehicles (> 43%) and the proportion decreased gradually with time (< 3% for Euro 5 and 6 vehicles). However, the proportion of diesel high-emitters had no correlation with the Euro standards.

The 2010 Colorado program (McClintock, 2011a) used two hits of CO, HC and NO cutpoints as the clean vehicle criteria. Over 250000 clean vehicle were identified by remote sensing in that program year, 98% of which were issued an exemption from the IM240 testing while 2% (4343) were randomly sampled for emission testing to evaluate the effectiveness of clean screening from remote sensing. The program showed that only 1.2% of the sample clean vehicles failed the IM240 inspection. It was estimated that 97.4% HC, 93.8% CO and 92.4% NO of program emission reductions were retained. The 2010 Texas study (McClintock, 2011b) compared the number of high-emitters identified by two criteria, namely the NCTCOG and DPS cutpoints. The results showed that 2.7% of gasoline and 1.5% of diesel vehicles were high-emitters in the NCTCOG cutpoints. The gasoline high-emitters

Table 4
Coverage and cutpoints of remote sensing screening studies.

Location and time	Fuel type and number of vehicles	Emissions measured and screening criteria	Reference
Illinois, 1990	Not discussed. 2929 measurements. 8 CO and 2 HC gasoline high-emitters selected for Test-and-Repair.	CO and HC. CO ≥ 4% and 1983 or newer.	(Rueff, 1992)
California, 1991	Not discussed. 60487 measurements. 3271 high-emitters identified, 307 roadside inspection.	CO and HC. Not discussed.	(Beaton et al., 1995; Bishop and Stedman, 1996)
Michigan, 1992 & California, 1991	Not discussed. 32945 vehicles in Michigan.	CO. CO > 4%.	(Stephens et al., 1997)
Utah, 1991, 1992	Not discussed. 17422 valid measurements. 114 high-emitters identified, 47 free repairs.	CO. Two hits of CO > 3%, 1965 or newer, registered in Utah county.	(Bishop et al., 1993)
Michigan, 1996	Not discussed. 73 late model GM vehicles.	CO, HC and NO. CO > 4% or HC > 0.3% or NO > 0.2%.	(Stephens et al., 1996)
Colorado, 1996–1997	Not discussed. 3189281 measurements.	CO. Good CO < 1.3%, Fair 1.3% < CO < 4.5%, Poor CO > 4.5%.	(Bishop et al., 2000)
Colorado, 1997–1998	Not discussed. 172633 measurements.	CO, HC and NO. Single hit of cutpoints: CO > 2–4%; HC > 200–2000 ppm; CO > 2% and HC > 200 ppm; CO > 3% and HC > 250 ppm; CO > 3% or HC > 250 ppm. Two hits of cutpoints: CO > 2.4–4%; HC > 200–500 ppm; CO > 3% or HC > 250 ppm.	(McClintock, 1999)
California, 2000	Not discussed. 67065 measurements. 18476 high-emitters identified, 306 pull-over testing.	CO, HC and NO. Pull-over test cutpoints: CO > 1% or HC > 500 ppm or NO > 500 ppm.	(BAR, 2001)
Michigan, 2007	Gasoline and diesel. 201504 measurements. 1373 high-emitters identified.	CO, HC, NO and PM. CO > 3% or HC > 500 ppm or NO > 2000 ppm or PM > 0.75.	(ESP and McClintock, 2007)
Colorado, 2010	Gasoline, diesel and other fossil fuels. > 9 million measurements. > 250000 clean vehicles identified, 2% (4343) I/M test.	CO, HC and NO. Two-hits of CO < 0.5% and HC < 200 ppm and NO < 1000 ppm.	(McClintock, 2011a)
Texas, 2010	Gasoline and diesel. 471771 measurements. 4719 high-emitters identified by NCTCOG.	CO, HC, NO and PM. DPS cutpoints (two hits): 1986–1990: HC ≥ 700 ppm or CO ≥ 4% or NO ≥ 4000 ppm 1991–1995: HC ≥ 500 ppm or CO ≥ 3% or NO ≥ 3500 ppm 1996–2008: HC ≥ 350 ppm or CO ≥ 3% or NO ≥ 3000 ppm NCTCOG Level 2 cutpoints (single hit): 1986–1991: HC ≥ 370 ppm or CO ≥ 2.8% or NO ≥ 2910 ppm 1992–1995: HC ≥ 296 ppm or CO ≥ 2.5% or NO ≥ 2328 ppm 1996–2001: HC ≥ 222 ppm or CO ≥ 2.5% or NO ≥ 2250 ppm ≥2002: HC ≥ 222 ppm or CO ≥ 1.68% or NO ≥ 1746 ppm	(McClintock, 2011b)
Vancouver, Canada, 2012	99% diesel. 98000 measurements.	CO, NO, HC and PM. Conservative cutpoints (g/kg): 1900–2007: NO > 45 or PM > 3.6 2008–2012: NO > 24 or PM > 2.4 Standards-based cutpoints (g/kg): 1900–1990: NO > 90 or PM > 6 1991–1997: NO > 45 or PM > 2.4 1998–2003: NO > 36 or PM > 1.8 2004–2007: NO > 30 or PM > 1.5 ≥2008: NO > 12 or PM > 0.9	(Environtest, 2013)
Madrid, Spain, 2014–2015	Gasoline and diesel. 196985 vehicles.	CO, HC and NO. $Q_{NO} > 88 \cdot 10^{-4}$ or $Q_{HC} > 80 \cdot 10^{-4}$ or $Q_{CO} > 0.18$ and VSP < 20kw/t.	(Pujadas et al., 2017)

identified by the lower NCTCOG cutpoints (2.7%) were double of that identified by the stricter DPS cutpoints (1.3%). However, the percentages of diesel high-emitters identified by the NCTCOG and DPS criteria were the same at 1.5%. The 2012 Vancouver study (Environtest, 2013) compared the effect of conservative and standards-based cutpoints on screening heavy-duty diesel high-emitters, showing that 8% vehicles were identified as high-emitters by the conservative cutpoints and 26% by the standard-based cutpoints.

These later remote sensing studies showed that the cutpoints or criteria for detecting high-emitting vehicles had significant effect on screening accuracy and the number of vehicles affected. However, the following limitations or findings need further investigation. Firstly, although recent studies (2007 or later) distinguished the vehicles by fuel type (gasoline or diesel), no verification was performed by laboratory or roadside testing. Therefore, the accuracy of remote sensing for diesel high-emitters has not been investigated yet. Secondly, the proportion of diesel high-emitters was not sensitive with the cutpoints (McClintock, 2011b) or emission standards (Pujadas et al., 2017). Thirdly, as shown in Table 4, most screening studies used emission percentages (% or ppm) as the cutpoints. As introduced in Section 2.1, the absolute emission percentages were calculated from the measured concentration ratios (Q_P) based on a key assumption that no oxygen remained in the exhaust, which was true for conventional gasoline vehicles but not for diesel and modern gasoline direct-injection stratified-charge vehicles. These limitations suggest that future investigations are needed for screening diesel or modern gasoline high-emitting vehicles.

Besides, the limitation that fixed cutpoints were used remained in these later studies, although some used different cutpoints for different model year vehicles. A fixed screening criterion for all passing by vehicles while not considering the road or driving conditions (e.g. road gradient, speed and acceleration) is not suitable. Several more sophisticated screening strategies have been proposed recently. Park and Rakha (2010) proposed a model for determining remote sensing cutpoints which considered vehicle speed and acceleration, as well as vehicle model year, weight and engine size. The proposed cutpoint model was effective for identifying high HC-CO and high HC-CO-NO vehicles but further improvement was needed for high NO and high CO vehicles. Rakha et al. (2010) developed a new approach to calculate the mass emission rates from the concentration ratios (Q_P) measured by remote sensing and the fuel consumption rates predicted by VT-Micro model which considered the vehicle category, speed, acceleration, model year and engine size. This approach demonstrated enhancement to the current high-emitter screening procedures. Zeng et al. (Guo et al., 2006; Zeng et al., 2006, 2008) developed an artificial neural network model for identifying high-emitters, which combined remote sensing and idle test data. However, field experiments, such as those in Table 4, are needed to verify these modelling studies.

It is important to recognize that vehicles with high instantaneous emissions do not mean they are permanent high-emitters. Clean vehicles may have high emissions occasionally, such as at load changes or during cold start. Since remote sensing only measures the emission snapshot in less than 1 s, the judgement of a vehicle being high-emitting or clean by a single remote sensing measurement is insufficient. Moreover, the uncertainties of remote sensing are relatively large. Therefore, additional filters are required to increase the screening accuracy of high-emitting or clean vehicles (Borken-Kleefeld, 2013), as the recommendations below.

1) Use remote sensing readings only in the moderate speed and moderate positive acceleration, or moderate vehicle specific power (VSP) range. Off-cycle driving conditions such as hard accelerations generate very high emissions but which do not mean the vehicle will fail the laboratory emissions testing.
2) Use cutpoints safely above emission levels of normal vehicles. Cutpoints can be made based on emission standards or previous remote sensing data, and should be detailed for each model year vehicles.
3) At least two hits of cutpoints are needed. For example, additional remote sensing devices can be placed after a certain distance from the primary measurement site.

Although a number of projects were conducted to investigate the use of remote sensing for high-emitter screening, few of them verified the accuracy in large scale and most of them were verified for gasoline vehicles. The case study in Hong Kong, which will be discussed in Section 4, showed that remote sensing worked accurately for screening gasoline high-emitters. However, frequent false detections were found for diesel vehicles. So far, no publication has been dedicated to investigate the screening accuracy of diesel vehicles, an important area requiring further research.

3.2. Monitoring emissions within vehicle fleets

Remote sensing can characterize the real-world emissions of a large vehicle fleet without constant human supervision, providing an ideal tool for monitoring on-road vehicle emissions in both the short and long term. With a large remote sensing database, it can generate very accurate results on the emission average and distribution within a vehicle fleet. These results are very useful for evaluating the effectiveness and performance of the emission standards, I/M programs, emission reduction technologies, and effect of vehicle age or mileage on emissions. So far, the majority of remote sensing studies were aimed at understanding fleet emission characteristics because they did not require legislative support like the high-emitter screening programs.

Table 5 summarizes a number of investigations studying emission characteristics using remote sensing which is shown to be quite flexible. As shown in Table 5, the size of the investigated fleet varied greatly from a few thousand (Baum et al., 2001; Stephens and Cadle, 1991) to over three million (Bishop et al., 2000) vehicles and the measurement time span changed from a few days (Baum et al., 2001; Bishop et al.,

Table 5
Summary of remote sensing studies for monitoring emission characteristics within vehicle fleets.

Location and time	Number of vehicles	Fuel type	Emissions measured	Reference
Colorado, 1/1989	3243 vehicles	Not discussed	CO	(Stephens and Cadle, 1991)
California, 1991	91679 measurements	Not discussed	CO and HC	(Beaton et al., 1995)
USA, Canada, UK, etc., 1991	> 200000 vehicles	Not discussed	CO	(Guenther et al., 1994)
Mexico City, 11–21/2/1991	34806 measurements	Not discussed	CO and HC	(Beaton et al., 1992)
Michigan, 1992	32945 cars	Not discussed	CO	(Stephens et al., 1997)
Utah, 11/11/1991, 27/1&30/3/1992	17422 valid measurements	Not discussed	CO	(Bishop et al., 1993)
Colorado, 16/5/1996-15/5/1997	3189281 measurements	Not discussed	CO	(Bishop et al., 2000)
Colorado, 4/1997-5/1998	172633 measurements	Not discussed	CO, HC and NO	(McClintock, 1999)
California, 25–30/4/1999	2091 vehicles	Gasoline	NH_3	(Baum et al., 2001)
Mexico City, 5/6–15/9/2000	122800 measurements	Gasoline and diesel	CO, HC and NO	(Schifter et al., 2003)
Taiwan, 10/1999-12/2000	528725 measurements	Not discussed	CO, HC and NO	(Ko and Cho, 2006)
Nevada, 2000–2002	188492 vehicles	Gasoline and diesel	CO, HC, NO and PM	(Mazzoleni et al., 2004a)
Auckland, New Zealand, 4/2003	42011 valid measurements	Gasoline and diesel	CO, HC and NO	(Xie et al., 2005)
Hangzhou China, 2004, 2005	32260 measurements	Gasoline	CO, HC and NO	(Guo et al., 2007b)
Colorado, Oklahoma, 2005	Not given	Gasoline and diesel	NH_3 and SO_2	(Burgard et al., 2006b)
Colorado, 17/8-2/9/2005	1641 valid measurements	Heavy-duty diesel trucks	CO, HC, NO, NO_2, SO_2, NH_3	(Burgard et al., 2006c)
Michigan, 23/4–25/52007	201504 measurements	Gasoline and diesel	CO, HC, NO and PM	(ESP and McClintock, 2007)
Illinois, Colorado, etc., 1997–2007	> 3/4 million measurements	Not discussed	CO, HC, and NO	(Bishop and Stedman, 2008)
Hong Kong, 2004, 2006, 2008	75% valid measurements	Gasoline, diesel and LPG	CO, HC and NO	(Lau et al., 2012)
California, 2008	70351 measurements	Gasoline and diesel	CO, HC, NO, NO_2 and NH_3	(Bishop et al., 2010)
UK, 2007–2010	84269 valid measurements	Gasoline and diesel	NO (estimated NOx)	(Carslaw et al., 2011)
Texas, 3/5-3/11/2010	471771 measurements	Gasoline and diesel	CO, HC, NO and PM	(McClintock, 2011b)
California, 12–16/8/2010	14691 measurements	Gasoline and diesel	CO, HC, NO, NO_2 and NH_3	(Bishop et al., 2012b)
Vancouver Canada, 55 days, 2012	98000 measurements	99% diesel	CO, NO, HC and PM	(Environtest, 2013)
Zurich Switzerland, 2000–2012	140400 vehicles	Gasoline and diesel	CO, HC, NO (estimated NOx)	(Chen and Borken-Kleefeld, 2014)
London UK, 21/5-2/7/2012	72712 measurements	Gasoline and diesel	NO, NO_2 and NH_3	(Carslaw and Rhys-Tyler, 2013)
Colorado, California, Oklahoma, 2005, 2008, 2013	144263 measurements	97% gasoline	NO, NO_2 and NH_3	(Bishop and Stedman, 2015b)
Illinois, 8–13/9/2014	20395 valid measurements	Not discussed	CO, HC, NO, NH_3 and NO_2	(Bishop and Stedman, 2015a)
Madrid Spain, 2014–2015	196985 vehicles	Gasoline and diesel	CO, HC and NO	(Pujadas et al., 2017)

2012b; Bishop and Stedman, 2015a) to over ten years (Bishop and Stedman, 2008; Chen and Borken-Kleefeld, 2014). Studies conducted in early years (before 1997) only measured CO and HC emissions and did not distinguish between gasoline and diesel vehicles in the fleets. The most important and repeatedly reported finding of early remote sensing studies was that the emission distribution was highly skewed within a vehicle fleet. That is, a small number of dirty vehicles were responsible for more than half the total fleet emissions, while the majority of clean vehicles only emitted very little emissions. This finding justified the effectiveness and importance of using remote sensing for identifying high-emitting or clean vehicles, instead of the conventional I/M programs which required all vehicles to take periodic inspections for emissions testing.

Fig. 3 demonstrated the skewness of CO, NO and HC emission distribution within a vehicle fleet in different cities. Two criteria were often used to quantify the skewness, namely what percentage of vehicles emitted half of the total fleet emissions (Criterion A) and what percentage of emissions were emitted by the dirtiest 10% vehicles (Criterion B). As shown in Fig. 3, generally, less than 10% of vehicles emitted half of the total fleet emissions or the dirtiest 10% vehicles accounted for more than half of the total emissions. However, Mexico City was an exception where half of CO and HC emissions were emitted by 24% and 12% of the vehicles in 1991 (Beaton et al., 1992) and the dirtiest 10% vehicles emitted 45% CO, 25% HC and 29% NO emissions in 2000 (Schifter et al., 2003). This was because the average emissions were higher and there were more gross polluters in Mexico City than other cities (Beaton et al., 1992). The emission distribution of gasoline fleets was more skewed than that of diesel fleets (Lau et al., 2012; McClintock, 2011b) and the skewness became more significant with the newer model year vehicles (Bishop and Stedman, 2015a). This skewed distribution also applied for PM (ESP and McClintock, 2007; Mazzoleni et al., 2004a; McClintock, 2011b) and NH_3 (Baum et al., 2001) emissions. Generally, CO and PM emissions were more skewed than NO and HC emissions. For example, Mazzoleni et al. (2004a) reported that the dirtiest 10% of vehicles contributed as much as 80% PM and 76% CO, but only 42% HC and 45% NO. It should be noted that the top 10% high-emitting vehicles responsible for half of each pollutant were different 10% vehicles due to the different/conflicting emission formation mechanisms. CO and HC emissions were the result of incomplete combustion (mainly in lean-oxygen condition) while NO emission was generated in high-temperature rich-oxygen conditions (Huang et al., 2015). In the 2010 California study (Bishop et al., 2012b), half of the

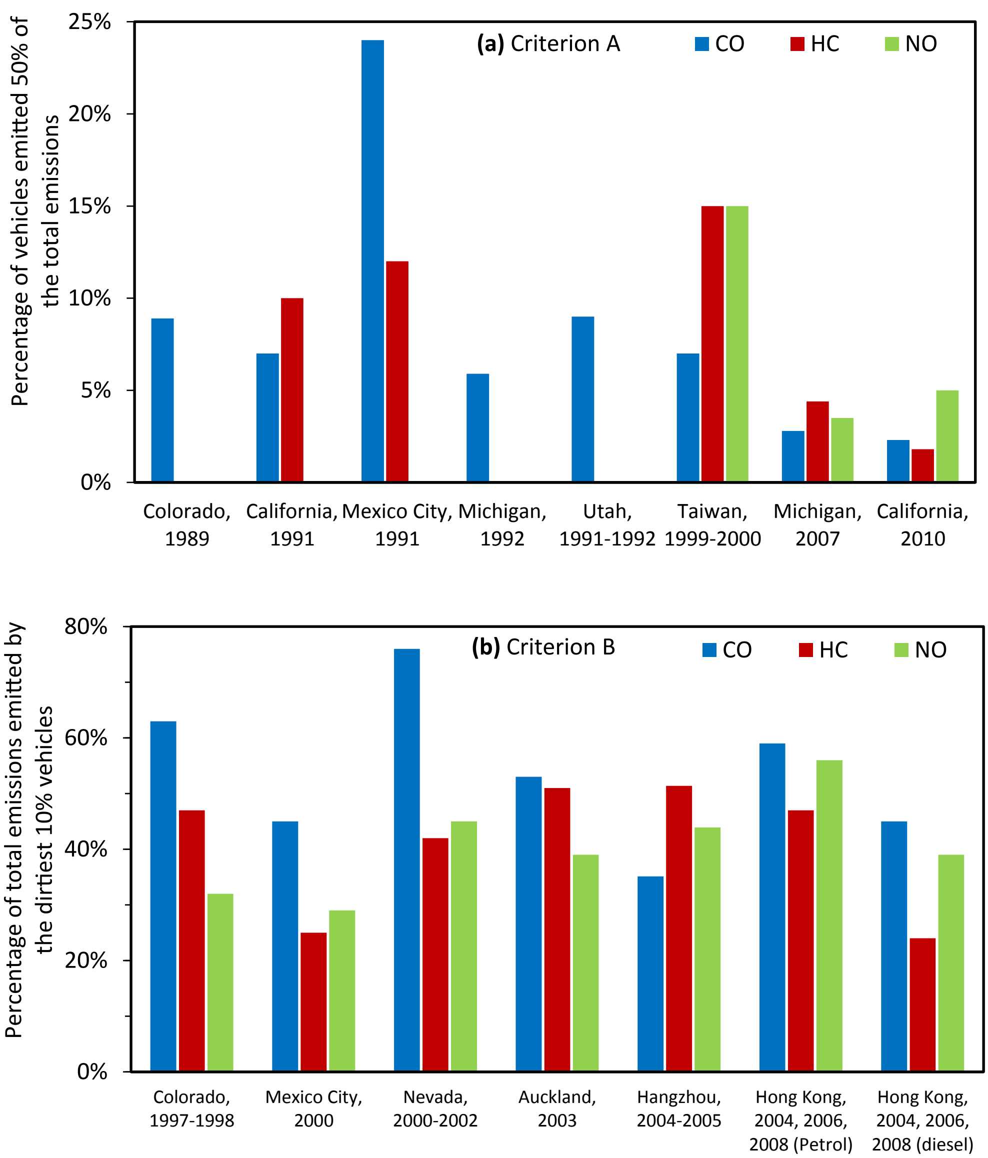

Fig. 3. Skewness of emission distribution within vehicle fleets. (a) Criterion A: percentage of vehicles emitting 50% of the total fleet emissions. (b) Criterion B: percentage of emissions being emitted by the dirtiest 10% vehicles.

fleet's total CO, HC and NO emissions were emitted by 2.3%, 1.8% and 5.0% of the dirtiest vehicles respectively. These high-emitters together accounted for 8.2% of the total fleet vehicles. However, they showed little overlapping, where only 7.1% of the high-emitters were high for both CO and HC, 2.6% were high for both CO and NO, 2.8% were high for both HC and NO, and 0.6% were high for all CO, HC and NO. The low overlapping proportion of high-emitters of each pollutant was also reported (Beaton et al., 1995; ESP and McClintock, 2007; Mazzoleni et al., 2004b).

Another main finding of early remote sensing studies was that emission levels increased with vehicle age and decreased steadily with newer model year (Bishop et al., 2010; Bishop and Stedman, 2008; Burgard et al., 2006b, 2006c; Schifter et al., 2003; Stephens and Cadle, 1991; Stephens et al., 1997), demonstrating the importance of proper maintenance and the effectiveness of the introduction of more stringent automotive emission standards. The increase of emission levels with vehicle age was mainly caused by a dramatic rise in the percentage of high-emitters (Bishop et al., 1993; Ko and Cho, 2006; Stephens et al., 1997), rather than an increase in the median vehicle emissions (Bishop et al., 1993). NH_3 was the only pollutant observed whose emission level decreased with the increase of vehicle age (Burgard et al., 2006b).

An important and concerning finding of the recent remote sensing studies was that while on-road CO and HC emissions were continuingly decreasing, NO_x emissions of diesel vehicles were not decreasing as expected, or even increased in recent years, despite the significantly tightened automotive emission standards. The 2004–2008 Hong Kong study found that CO and NO emissions of modern diesel vehicles were similar to those of older vehicles (Lau et al., 2012). A 13-year study (2000–2012) in Zurich (Switzerland) showed that NO_x emissions of both diesel cars and diesel light commercial vehicles were actually increased (Chen and Borken-Kleefeld, 2014). The 2007–2010 UK study showed that NO_x emissions of gasoline vehicles reduced substantially during 2005–2010, but NO_x emissions of diesel vehicles tended to increase during 1987–2010 (Carslaw et al., 2011). A following remote sensing study in 2012 by the same UK team confirmed that all types of diesel vehicles had little NO_x reduction over the past 15–20 years including those with NO_x after-treatment systems, while gasoline passenger cars (including hybrids) showed considerable reduction in NO_x (Carslaw and Rhys-Tyler, 2013). The 2014–2015 Madrid (Spain) study showed that CO and HC emissions from gasoline and diesel engines were gradually reducing (Pujadas et al., 2017). On the other hand, NO emission of gasoline engines was progressively reduced, while NO emission of diesel engines did not decrease.

The emission standards are complied with laboratory testing. This unexpected increase of NO_x emissions in diesel engines was mainly caused by the significant discrepancy between the real-driving and homologation test procedure engine conditions. Therefore it was suggested that the European emission standards or NEDC needed to be revised to reflect the actual driving conditions better than it currently does (Carslaw et al., 2011). Besides, the rated maximum power output of petrol cars remained almost constant over the past 20 years, while the power of diesel cars had increased markedly by about 50% (Carslaw et al., 2013). As NO_x emissions had strong dependency on VSP, this power increase might help explain the increased NO_x emissions of modern diesel vehicles. In North America, the reduction in NO emission was also occurring at a lower rate than other emissions (Bishop and Stedman, 2015a; Environtest, 2013).

Regarding the emission characteristics of different vehicle classes, recent remote sensing studies reported that diesel vehicles had much higher NO and PM emissions but lower CO emissions than gasoline vehicles did (Environtest, 2013; ESP and McClintock, 2007; Lau et al., 2012; McClintock, 2011b).

3.3. Development of EFs and models

The estimation of road traffic emission inventories is critical for setting and evaluating environmental policies such as air quality and vehicle emission standards (Smit et al., 2010), which requires accurate emission models. Emission models are aimed to provide appropriate EFs which are functional relations that predict the quantity of a pollutant emitted per distance travelled or amount of fuel consumed (Franco et al., 2013). EFs usually take into account a number of parameters, including vehicle class, fuel type, emission control technology and driving conditions. The representativeness of EFs greatly determines the quality of emission models (Franco et al., 2013). On-road remote sensing can simultaneously measure various exhaust emissions with the vehicle information and driving conditions in a large scale under real-world driving conditions. These features make remote sensing data very valuable for developing real-world EFs. As introduced in Section 2.1, fuel based EFs in [g/kg fuel] can be calculated from remote sensing data. Hence, the emission inventory of the total fleet can be obtained by multiplying the overall EF with the mass of fuel consumed by that fleet, which is available from tax records (Pokharel et al., 2002).

The EFs calculated by equations 10–12 have been widely used to estimate the emissions of individual vehicles, mean emissions of vehicle subgroups and fleet emission inventories. Table 6 lists various EFs derived from remote sensing data. Jimenez et al. (2000) estimated the NO_x EF of a small heavy-duty diesel truck fleet (73 vehicles) in North Carolina. Zhou et al. (2014) calculated the fuel and distance based EFs for light-duty gasoline vehicles and motorcycles in Macao. Singer and Harley (1996) estimated the overall fleet-average CO EF by taking into account the travel fractions and average EF of each vehicle subgroup (model year, vehicle class). The CO emission inventory was calculated by multiplying the fleet-average EF with the total gasoline consumed. The same method was used to estimate the fleet-average EFs and total emission inventories of CO, HC and NO in Denver (Pokharel et al., 2002), Mexico City (Schifter et al., 2005) and Hangzhou (Guo et al., 2007b).

However, the above EFs did not take into account the driving conditions such as vehicle speed and acceleration. Several studies were performed to include these parameters in the estimation of EFs. Yu (1998) used four independent parameters in regression analysis of CO and HC EFs, including speed (u), speed-squared (u^2), acceleration (a) and acceleration-squared (a^2). This method was applied to estimate CO, HC and NO EFs for gasoline (Chan et al., 2004), diesel (Chan and Ning, 2005) and liquefied petroleum gas (LPG) (Ning and Chan, 2007) vehicles in Hong Kong. In addition, fuel economy (FE) factors correlated to vehicle speed were used for different fuel type vehicles (Chan and Ning, 2005; Chan et al., 2004; Ning and Chan, 2007). FE factors could also be expressed as a function of vehicle speed and acceleration (Lau et al., 2012). Recently, Li et al. (2016) used artificial neural networks to estimate fuel-based EFs of CO, HC and NO from remote sensing data, which considered the driving patterns and meteorological conditions. Although emission models/factors were becoming more complex and comprehensive with time, statistical analysis showed that more complex models did not perform better than less complex models in terms of prediction error (Smit et al., 2010).

Since on-road remote sensing measurements often covered a large and random sample of vehicles, the derived EFs represented an independent method for verifying the traditional emission inventory models developed from other emission measurement technologies (Singer and Harley, 1996). Ekström et al. (2004) evaluated the COPERT III emissions model by remote sensing in Gothenburg (Sweden) and observed that the agreement between the model and remote sensing was good for NO_x, moderate for HC and poor for CO. The International Vehicle Emissions (IVE) model was evaluated by remote sensing in Hangzhou (China) (Guo et al., 2007a). It was reported that IVE model predicted HC well, but under-predicted CO by 12%–50% and over-predicted NO_x by 50%–250% for gasoline passenger cars. Kuhns et al. (2004) compared the EFs measured by remote sensing with the MOBILE6 and PART5 models. The results showed that MOBILE6 modelled HC well for vehicles less than 20 years old, over-predicted CO by two

Table 6
EFs developed from remote sensing data.

Remote sensing data	Vehicle type	EFs *	Reference
7 sites in California, 1991 > 70000 vehicles CO and HC	Gasoline cars and trucks	Individual $EF_{CO} = \frac{Q_{CO}}{1+Q_{CO}+3Q_{HC}} * \rho_f * \frac{28}{M_f}$ [g/gal fuel] Fraction of vehicle subgroup $f_{yv} = \frac{n_{yv}/N/FE_{yv}}{\sum_{y=1}^{Yn}\sum_{v=1}^{Vn} n_{yv}/N/FE_{yv}}$ Fleet average $EF_{CO} = \sum_{y=1}^{Yn}\sum_{v=1}^{Vn} f_{yv} E_{CO,yv}$	(Singer and Harley, 1996)
5 sites in Houston, 1996 CO and HC	Passenger cars; Van and pick-up trucks; Other trucks	$EF_{P,\ v} = c_1/u + c_2 + + c_3u + c_4a/u + c_5a^2/u$ [g/mile]	(Yu, 1998)
1 site in North Carolina, 1997 73 vehicles NO	Heavy-duty diesel trucks	$EF_{NOx\ (as\ NO2)} = 45 \pm 2$ [g/kg fuel]	(Jimenez et al., 2000)
Denver, 1999–2000 10-2000 measurements in each subgroup CO, HC and NO	Cars and trucks	Individual $E_{CO} = 28 * Q_{CO}/(Q_{CO}+1 + 6.6Q_{HC}) * 71.4$ [g/kg fuel] Individual $E_{HC} = 44 * 2.2 * Q_{HC}/(Q_{CO}+1 + 6.6Q_{HC}) * 71.4$ [g/kg fuel] Individual $E_{NO} = 30 * Q_{NO}/(Q_{CO}+1 + 6.6Q_{HC}) * 71.4$ [g/kg fuel] Relative fuel use of subgroup $f_{yv} = \frac{n_{yv}/N/FE_{yv}}{\sum_{v=V1}^{Vn}\sum_{y=Y1}^{Yn}(n_{yv}/N/FE_{yv})}$ Overall $EF_P = \sum_{v=V1}^{Vn}\sum_{y=Y1}^{Yn} f_{yv} EF_{P,yv}$	(Pokharel et al., 2002)
12 sites in Mexico City, 2000 42822 valid measurements CO, HC and NO	light-duty vehicles	Average $EF_{CO} = 113.5 \pm 13$ [g/L fuel] Average $EF_{HC} = 13.1 \pm 1.9$ [g/L fuel] Average $EF_{NOx} = 9.84 \pm 2.3$ [g/L fuel]	(Schifter et al., 2005)
9 sites in Hong Kong, 2001 8544 valid measurements CO, HC and NO	Gasoline vehicles	$Q_P = c_1 + c_2u + c_3u^2 + c_4a + c_5a^2$ $EF_{CO} = 1200 * Q_{CO}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $EF_{HC} = 3651 * Q_{HC}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $EF_{NO} = 1293 * Q_{NO}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $EF_P = E_P * 0.8504 * u^{-0.674}$ [g/km]	(Chan et al., 2004)
9 sites in Hong Kong, 2001 6321 valid measurements CO, HC and NO	Diesel vehicles	$Q_P = c_1 + c_2u + c_3u^2 + c_4a + c_5a^2$ $E_{CO} = 1718 * Q_{CO}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $E_{HC} = 5477 * Q_{HC}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $E_{NO} = 1841 * Q_{NO}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $EF_P = E_P * 3.1995 * u^{-1.1131}$ [g/km]	(Chan and Ning, 2005)
5 sites in Hangzhou, 2004–2005 32260 vehicles CO, HC and NO	Gasoline vehicles	Individual $EF_P = \frac{Q_P}{1+Q_{CO}+4Q_{HC}} * \frac{M_P \rho_f}{M_f}$ [g/L fuel] Relative fuel use of subgroup $f_i = \frac{n_i/N/FE_i}{\sum n_i/N/FE_i}$ Overall $EF = \sum_{i=1}^{n} EF_i = \sum_{i=1}^{n} EF_i f_i$	(Guo et al., 2007b)
Hong Kong, 2006 1791 valid measurements of a 20-taxis fleet CO, HC and NO	LPG vehicles	$Q_P = c_1 + c_2u + c_3u^2 + c_4a + c_5a^2$ $EF_{CO} = 1076 * Q_{CO}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $EF_{HC} = 3429 * Q_{HC}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $EF_{NO} = 1153 * Q_{NO}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $EF_P = E_P * 0.36617 * u^{-0.2988}$ [g/km]	(Ning and Chan, 2007)
10 sites in Hong Kong, 2004, 2006, 2008 75% valid measurements CO, HC and NO	Gasoline, diesel and LPG vehicles	Fuel based $EF_{P1} = \frac{P}{CO + CO2 + 6 * HC} * \frac{M_P * \rho_f}{M_{fuel}}$ [g/L fuel] Distance based $EF_{P2} = EF_{P1} * FE$ [g/km] $FE_{gasoline} = 0.135 + 2.017/u + 0.029a$ [L/km] $FE_{diesel} = 0.066 + 1.034/u + 0.042a$ [L/km] $FE_{LPG} = 0.153 + 3.296/u + 0.025a$ [L/km]	(Lau et al., 2012)
19 sites in Macao, 2008 CO, HC and NO	Light-duty motorcycles (LDMC), heavy-duty motorcycles (HDMC), and light-duty gasoline vehicles (LDGV)	$E_{CO} = 1200 * Q_{CO}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $E_{HC} = 1800 * Q_{HC}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $E_{NO} = 1293 * Q_{NO}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $EF_P = FE * E_P$ [g/km] FE = 2.0 (LDMC), 2.8 (HDMC), 8.5 (LDGV) [L/100 km]	(Zhou et al., 2014)
Hefei, 2012 38867 valid measurements CO, HC and NO	light-duty gasoline vehicles	$E_{CO} = 1200 * Q_{CO}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $E_{HC} = 1800/0.493 * Q_{HC}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] $E_{NO} = 1293 * Q_{NO}/(1+Q_{CO}+6.1Q_{HC})$ [g/L fuel] Back-propagation and Radial basis function neural networks	(Li et al., 2016)

**Symbols*: c_1-c_5: regression coefficients; y: model year; v: vehicle type; n_{yv}: number of vehicles in subgroup (y,v); N: total number of vehicles.

times for vehicles less than 13 years, and under-predicted NO by 33% for 7–15 years vehicles but agreed well for vehicles less than 7 years. PART5 only predicted a constant PM EF which was about the value of 13-year-old vehicles. Fujita et al. (2012) compared the fleet-averaged EFs of tunnel and remote sensing measurements with those modelled by MOVES2010a, MOBILE 6.2 and EMFAC 2007. The modelled CO and NO_x EFs were in reasonable agreement (± 25%). However, the measured HC/NO_x ratios were 1.4–3.1 times higher than those predicted by the three models during high-temperature periods. These studies highlighted that each EF model was only accurate for some pollutants under specific conditions, but had limitations of significant over- or under-estimation for other pollutants.

3.4. Evaluation of emission control programs and technologies

The large sampling size of vehicle emissions under real-world driving conditions makes remote sensing an effective and economic tool to evaluate the performance of emission control programs and technologies. Many early remote sensing studies were developed in parallel with the US vehicle emissions regulatory practices, particularly the introduction of I/M programs (Ropkins et al., 2009). I/M programs were aimed to improve air quality by identifying cars and trucks with high emissions that might need repairs. The 1990 Amendments to the Clean Air Act made I/M mandatory for several areas across the US. A number of remote sensing studies were conducted to evaluate the performance and effectiveness of I/M programs (Lawson et al., 1990; Stedman et al., 1997, 1998; Zhang et al., 1993, 1996b), and provided valuable experimental data on the performance and limitations of I/M programs. For example, Zhang et al. (1993) found that CO emissions of I/M vehicles were 13% lower than those of non-I/M vehicles, while no significant difference was observed in HC emissions. Bishop et al. (1997) observed a steady emission reduction after the introduction of light-duty vehicle emission standards and the implementation of I/M programs in Mexico. Stedman et al. (1997) reported that the benefits of a one-year-old I/M program in Colorado were significant for CO emissions, but undetectable for HC and NO emissions. Guenther et al. (1994) compared the remote sensing data measured in the USA, Canada, Mexico, UK and Sweden and concluded that the USA Federal New Vehicle Emissions Standards had caused a dramatic reduction in fleet emissions. However, Zhang et al. (1996b) concluded that the performance of the past I/M programs on reducing CO and HC emissions was less effective than that predicted by the US EPA.

Regarding the effect of I/M programs on high-emitters, Lawson et al. (1990) found that CO and HC emissions from high-emitters were much higher than when the vehicles received their routine inspection, and the time since the I/M program had little influence on the cars' emissions in the roadside inspection. A remote sensing study in Denver showed that some high-emitting vehicles were registered outside the I/M area after they failed the I/M test but they were still driven in the I/M area, which might have reduced the benefits of I/M programs (Stedman et al., 1998).

To achieve air quality targets, other emission control programs were also frequently implemented, such as new emission control technologies, fleet retrofits, and reformulated and oxygenated fuels. Remote sensing data were valuable to assess the performance of these programs as well.

Burgard and Provinsal (2009) measured the CO, HC, NO and NO_2 emissions of school buses equipped with 5-year old diesel oxidation catalysts (DOC) and diesel particulate filters (DPF) by remote sensing. The results showed that CO and HC emissions decreased while NO_x, NO and NO_2/NO_x ratio increased with each retrofit technology. Sjödin (1994) used remote sensing to investigate the emission performance of three-way catalysts (TWC) and non-catalyst cars. It was found that the average CO emission of TWC cars was about 90% lower than that of non-catalyst cars. However, the reduction of HC emission was uncertain due to the presence of liquid water in the exhaust which interfered with the HC measurement. A later remote sensing study of Sjödin and Andréasson (2000) reported that the emission performance of new TWC-cars had improved significantly in recent years. A decade of on-road remote sensing measurements in the USA showed large and fuel specific reductions for CO, HC and NO emissions, implying that the emission reductions were mainly due to continued improvements in the function and durability of vehicle emission control systems, while I/M and fuel reformulation programs only played a minor role (Bishop and Stedman, 2008).

For fleet retrofit and air quality programs, Bishop et al. (2012a) assessed the retirement program of heavy-duty diesel trucks fleet in California by remote sensing. They found that the mean fleet age decreased from 12.7 years in April 2008 to 2.5 years in May 2010 with significant reductions in CO, NO_x and PM emissions. Bishop et al. (2013) also evaluated the effect of California and Federal emission regulations for 2007 and newer heavy-duty diesel engines. The remote sensing data showed that NO_x emissions had decreased by 12% since 2010, while PM emissions remained low, indicating no deterioration of the DPF. Dohanich et al. (2004) investigated the associations between CO, HC and NO emissions and vehicle year (1926–2000) by remote sensing. The results showed that the median emissions of five-year categories peaked in the 1950s and decreased steadily thereafter, with the steepest declines from the late 1970s to early 1980s. This emission decrease was in line with the advances in emission control technology, oxygenated gasoline, more fuel-efficient engines and emission testing.

Zhou et al. (2007) used remote sensing to evaluate the effectiveness of the vehicle emission control measures that aimed to improve Beijing's air quality. The results showed that aggressive control strategies that were recently implemented significantly reduced on-road emissions, while the earlier program to retrofit pre-Euro cars with TWC produced little emission reduction. The results also implied that the durability of vehicle emission controls may be inadequate.

Regarding the performance of reformulated and oxygenated fuel programs, remote sensing data showed that the Colorado Oxygenated Fuels Program had led to a statistically significant decrease in the average CO emission (Bishop and Stedman, 1989, 1990). Baum et al. (2000) used remote sensing to measure the emissions of vehicles powered by reformulated Phase II gasoline, diesel, compressed natural gas and methanol blended with 15% gasoline. They found that the gasoline and methanol powered cars had increased NH_3 emission. Installation of TWC showed high reduction activity in some vehicles but poor selectivity resulted in the formation of NH_3 and possibly other nitrogen-containing products.

Remote sensing can be used to do comparison or cross checks with other emission testing technologies. Lawson et al. (1990) conducted a double-blind comparison on the CO emissions measured by remote sensing and on-board emission analyser, showing an accuracy of $\pm$ 10% for remote sensing. Bishop et al. (1996b) studied the test-to-test variability of different emission testing methods, including FTP, IM240 dynamometer testing, idle testing and remote sensing. They found that the variability was attributed to the vehicle, not to the testing procedure. Scheduled I/M programs would fail to identify and repair these vehicles, resulting in a large percentage of high-emitting vehicles to escaping the reduction measures. The only way of reliable detection of high-emitting vehicles was through multiple tests. Bishop et al. (1996a) compared the vehicle emissions in a tunnel measured by remote sensing, bags, canisters, adsorbent traps and Fourier transform infrared spectroscopy. Walsh et al. (1996) compared the vehicle emissions of three measurement techniques, including two-speed idle testing, remote sensing and IM240 dynamometer testing. The results showed good agreement between the three methods, but site selection and cutpoints must be carefully considered when using remote sensing for the detection of high-emitting vehicles. Yanowitz et al. (2000) compared the emission measurements from chassis dynamometer, remote sensing, and tunnel study for heavy-duty diesel vehicles. The three techniques showed reasonable agreement between NO_x emissions, but the agreement for CO, HC and PM emissions was qualitative. Westerdahl et al. (2009) compared the CO emission factors derived from measurements in three different environments (on-road, roadside and ambient) with those from remote sensing in Beijing (China) and observed a good agreement. Smit and Bluett (2011) proposed a new method to compare vehicle emissions measured by remote sensing and laboratory testing. The results showed that laboratory and remote sensing data are substantially different for CO, HC and NO_x emissions in terms of their distributions, mean and 99th percentile values. It implied that high-emitters might not be adequately captured in laboratory testing.

Remote sensing can also be applied to evaluate the effect of some real-world factors on vehicle emissions that would be difficult or costly to achieve with laboratory testing. For example, remote sensing was used to investigate the effect of altitude on CO, HC and NO emissions of heavy-duty diesel trucks (Bishop et al., 2001b). The results showed that the emissions increased with the increase of altitude. Long-term remote sensing data was used to investigate the deterioration rates of emission control systems of both gasoline (Borken-Kleefeld and Chen, 2015) and diesel (Chen and Borken-Kleefeld, 2016) cars in Zurich (Switzerland). They found that deterioration rates for hot NO_x and CO emissions of older gasoline vehicles were much lower than assumed, but significantly higher for Euro 3 and 4 cars. Moreover, the deterioration rates did not depend on engine load. Regarding diesel cars, the NO_x emission rates were stable over the mandatory durability interval of

80000 km for Euro 1 and 4 cars, but were about 23–25% for Euro 2 cars and 5–11% for Euro 3 cars. Bishop et al. (2016) investigated the effect of mileage (age) on fleet emissions and found that the small high-mileage fleets (e.g. taxi and shuttle vans) might have emitted a significant share of the total emissions.

3.5. Remote sensing of off-road emissions

Although remote sensing was mainly developed for on-road vehicle emissions, the technology is also applicable to measure off-road emissions. Bishop et al., 1999, 2001a, 2006 used remote sensing to measure CO and HC emissions of snowmobiles in the Yellowstone National Park. Remote sensing technique had also been applied to measure the NO emission from in-use aircrafts while on the ground (Popp et al., 1999b) and railway locomotives (Popp et al., 1999c). Recently, Burgard et al. (Burgard and Bria, 2016; Burgard et al., 2011) expanded the application of remote sensing to measure CO, HC, NO, NO_2 and SO_2 emissions of marine ships. However, these applications were rather few compared with on-road emission measurements due to the less regulatory attention and public concern on off-road emissions.

4. Experience and issues of remote sensing application in Hong Kong

Hong Kong is one of the first megacities where remote sensing has been extensively tested since 1993 under the auspices of the Hong Kong Environmental Protection Department (HKEPD) and is currently used for regulatory enforcement. There is therefore a wealth of vehicle emission data from Hong Kong using remote sensing, which should be evaluated and shared with the research community, in an effort to improve the accuracy and application of remote sensing of on-road vehicle emissions.

Remote sensing has been used for various applications in Hong Kong. It was used to develop real-world EFs of CO, HC and NO for gasoline (Chan et al., 2004), diesel (Chan and Ning, 2005) and LPG (Ning and Chan, 2007) vehicles. The results showed that the vehicle model year, engine size and driving pattern had a strong correlation with their EFs. Remote sensing was also used to monitor vehicle emissions in Hong Kong. A remote sensing study that took place in 22 cities worldwide during 1990–1994 reported that Hong Kong had lower CO and HC emissions than other cities (Zhang et al., 1995). Lau et al. (2012) analysed the remote sensing data collected in 2004, 2006 and 2008. The results showed that LPG vehicles generally had higher emissions compared to gasoline and diesel vehicles, particularly among high-emitting vehicles. In addition, while emissions of gasoline and LPG vehicles were continuously decreasing, CO and NO emissions of diesel vehicles increased during 2004–2008. A recent diesel remote sensing study (Huang et al., 2018) reported that CO, HC and NO emissions showed an unexpected increasing trend during 1998–2004, but they all decreased steadily during 2005–2015 except for NO of ≥6001 cc vehicles during 2013–2015.

From 1 September 2014, the HKEPD started to use remote sensing as an enforcement tool for detecting high-emitting vehicles in Hong Kong (HKEPD, accessed 18.05.2017). Fig. 4 illustrates the procedures of the HKEPD enforcement program, which utilised two sets of remote sensing equipment that were placed with 1-s distance on a slight incline. All the data was transmitted to a remote data storage and then post processed by the HKEPD to identify the vehicle manufacture year, model, fuel type and emission certification levels. For a vehicle to be identified as a high-emitter, there must be two measurements above the cutpoints and the driving characteristics must be within the speed/acceleration ranges of the laboratory testing cycle. Further to this, the measurement data would be rejected if the traffic was near to standstill (< 10 km/h). The cutpoints were determined based on a significant database of remote sensing and chassis dynamometer measurements, from which a correlation between the emission levels of a vehicle when emitting the highest transient concentrations and still being able to pass a chassis dynamometer test was derived. The next step was for the vehicle owner to be notified via an Emission Test Notice (ETN) that the vehicle was detected with high emissions and must be serviced/repaired and tested at an authorised Emissions Testing Centre within 12 working days. The high-emitting vehicles were required to pass a short transient chassis dynamometer emission test, the Hong Kong Transient Emission Test (HKTET), to remain registered and roadworthy.

Before the enforcement program began, there was a particular focus on LPG vehicles which were used for public transport purposes in Hong Kong, i.e. taxis and minibuses. These vehicles accumulate a high mileage quickly and the performance of their TWCs and oxygen sensors can deteriorate significantly within two years from new. It was suspected that a significant number of these vehicles would be detected as high-emitters and possibly fail the HKTET as the fleet average age was between 5 and 10 years. Two main actions were taken to support the industry to clean up the fleet, including a one-time replacement program of TWCs and oxygen sensors and a series of seminars and workshops to teach mechanics what to check and repair. The industry took receipt of approximately 17000 sets of TWCs and oxygen sensors for taxis and minibuses.

The remote sensing program in Hong Kong has been very effective in tackling the excessive emission problems of gasoline and LPG vehicles. Over 1.6 million vehicle measurements have been taken in Hong Kong from the enforcement start date (1 September 2014) till 30 April 2017. As shown in Table 7, 8207 ETNs were issued and 95% of the high-emitting vehicles have been successfully repaired and passed the HKTET. In total, 356 vehicles had their licences cancelled for either failing the HKTET or not conducting the test. The percentages of gasoline and LPG high-emitting vehicles had been reduced from 10% and 80% to 5% and 20% between 2014 and 2016, respectively. HKEPD (2017) reported that the roadside concentrations of PM_{10}, $PM_{2.5}$, NO_x, NO_2 and SO_2 were reduced by 16%, 13%, 12%, 17% and 13% during

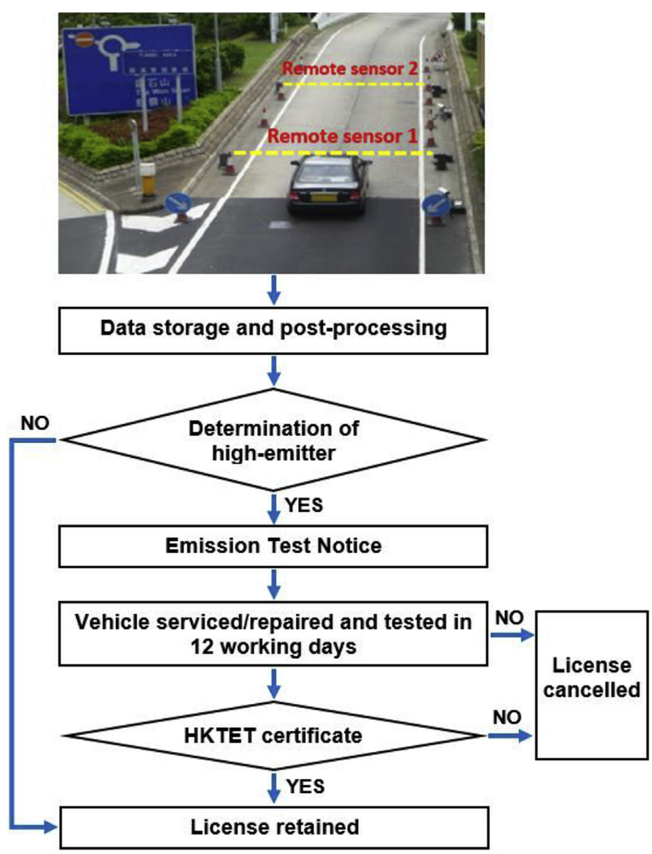

Fig. 4. The process of the HKEPD remote sensing enforcement program.

Table 7
Statistics on Hong Kong remote sensing enforcement program (1/9/2014–30/4/2017).

	Vehicle Type	Number of vehicles	Percentage
Emission Testing Notice (8207 in total)	Light goods vehicle	22	0.3%
	Private car	2396	29.2%
	Light bus	428	5.2%
	Taxi	5361	65.3%
HKTET test result (7573 in total)	Repaired and passed HKTET	7217	95.3%
	Failed HKTET and licence cancelled	162	2.1%
	Not conducting HKTET and licence cancelled	194	2.6%

2015–2016, respectively.

However, a major limitation is that the HKEPD enforcement program is only limited to gasoline and LPG vehicles, while diesel vehicles - a major source for NO_x and PM emissions - are excluded. Remote sensing as it is currently utilised produces significant false detections of diesel high-emitters. The reasons for the discrepancy between on-road remote sensing measurement and laboratory chassis dynamometer test and the suggested research path that could provide the answers are discussed as follows.

Firstly, diesel vehicles have much lower CO and HC emissions but higher NO_x emissions than gasoline vehicles do. Fig. 5 shows the emission percentiles of 88 pass and 98 failed diesel vans. Two times the respective standard limits are the suggested selection criteria determining failed vehicles in Hong Kong. Each vehicle was tested in the 200-s HKTET test (Commissioner for Transport, 2012). As shown in Fig. 5, CO and HC concentrations of both pass and failed vehicles are relatively low. Compared with Table 3, the range of CO is about the same as the uncertainly of remote sensing device and the range of HC is even much lower than the device uncertainty. In addition, the emission concentrations of failed vehicles are not significantly different to those of pass vehicles, in particular CO and HC emissions. The failed vehicles have a large proportion of time with emissions lower than the maximum emission levels of pass vehicles. The 99th emission percentiles of pass vehicles equal to the 95th CO, 96th HC and 75th NO_x of failed vehicles. This means, if the 99th emission percentile levels of pass vehicles are used as the cutpoints, a high-emitter will only have 5%, 4% and 25% of chance to be identified as high-emitting in CO, HC and NO_x by a snapshot remote sensing measurement, respectively. The above results imply that the enforcement program for diesel vehicles may focus on NO_x emissions which are more detectable and important. Another research path is to improve the accuracy of current remote sensing device. The HKEPD is now developing a new generation of remote sensing device with higher sensitivity so that identification of diesel high-emitters can be feasible.

Secondly, gasoline and diesel engines have different operating principles. Gasoline engines, also referred to as spark ignition (SI) engines, control the output power by adjusting the fuel injection rate (through injection duration and pressure) and intake air flow rate (through a throttle valve), in which the combustion is always around stoichiometric conditions. However, diesel engines, also referred to as compression ignition (CI) engines, do not have a throttle valve and the output power is controlled by only changing the fuel injection rate. As a result, diesel engines are always operated under lean conditions, even at full load (Heywood, 1988). As introduced in Section 2.4, a limitation of remote sensing is that it cannot distinguish the excess oxygen in the exhaust from the large amount of oxygen in the atmosphere (Burgard et al., 2006a). This results in inaccurate calculation of absolute emission concentrations, which is based on a key assumption that the engine is running rich with no oxygen in the exhaust (Bishop and Stedman, 1996; Burgard et al., 2006a). In the current HKEPD enforcement program, the emission concentrations calculated from remote sensing data were compared with the cutpoints in absolute concentrations (the same in other high-emitter screening programs, as shown in Table 4). This would consequently lead to the frequent false detections of diesel high-emitters. This implies that the cutpoints for diesel high-emitters should be in concentration ratios (Q_P) or emission factors (g/kg fuel) which remove the assumption. Research is needed to establish the correlations between remote sensing and HKTET data for both pass and failed diesel vehicles so that accurate determination of high-emitters based on one remote sensing measurement is possible.

For the issue of remote sensing for diesel high-emitters, there is a lack of study in this area which usually requires legislative support. Although remote sensing has been used globally for other purposes (Sections 3.2–3.5), the majority of these studies merely used remote sensing as a tool to measure on-road vehicle emissions, involving no laboratory testing for validation. For the application of detecting high-emitting vehicles, as reviewed in Section 3.1, it was mainly used in the USA to assist the I/M programs, where the majority of passenger cars were gasoline fuelled. Early studies (Beaton et al., 1995; Bishop and Stedman, 1996; Rueff, 1992) have validated the accuracy of

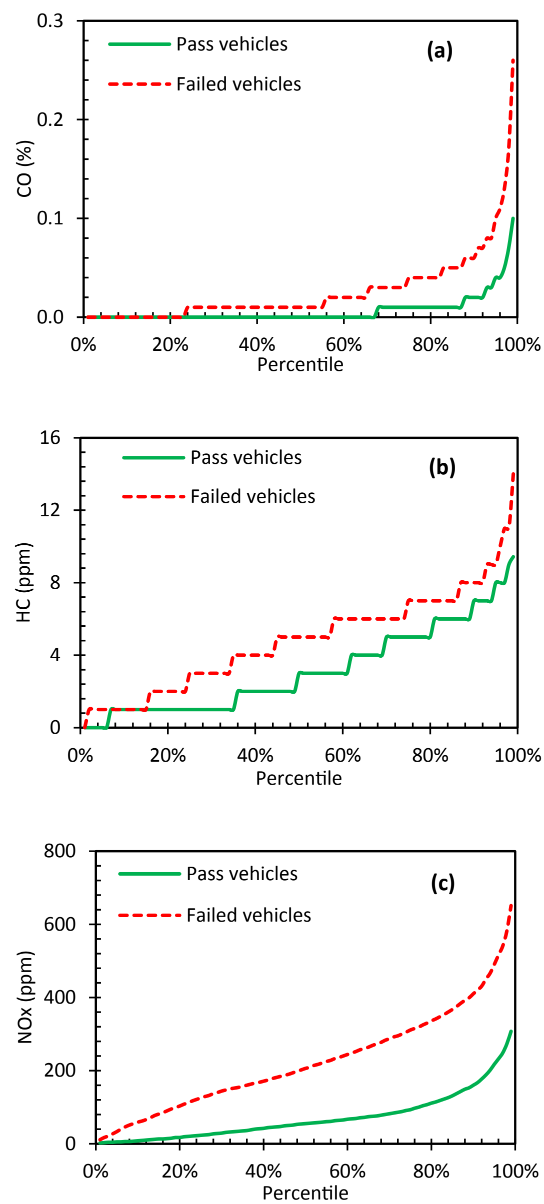

Fig. 5. CO (a), HC (b) and NOx (c) emission percentiles of pass and failed diesel vans in Hong Kong.

identification of high-emitters by roadside or laboratory testing. However, the vehicles used were few and all gasoline vehicles. Later studies (Environtest, 2013; ESP and McClintock, 2007; McClintock, 2011b; Pujadas et al., 2017) investigated the use of remote sensing for diesel high-emitters, but no validation by roadside or laboratory testing was conducted. Therefore, to the best of the authors' knowledge, so far no publication has reported the issue of remote sensing for diesel high-emitters. HKEPD is conducting multiple projects to research the performance of diesel vehicles so characterisation of emissions for different vehicle classes is established. Research into remote sensing to support this is also being undertaken with the goal to be able to utilise it for all vehicles on Hong Kong roads.

5. Challenges and future perspectives

Air quality is deteriorating in many countries, leading to serious concerns for public health and the need for more stringent regulations on air quality and vehicle emissions. Rapidly increasing traffic levels have contributed to a significant proportion of air pollution. Although strict and even aggressive measures (e.g. ordering half of all private cars off the road in some Chinese cities when haze occurred in winter) are taken to address the issue of air pollution, the problem does not seem to be solved satisfactorily. Therefore, understanding vehicle emissions and then controlling them are becoming an important challenge of modern society. On-road remote sensing has been proven an effective and economic tool in monitoring and controlling automotive emissions. As discussed in Section 3, remote sensing has been successfully used globally for various applications. However, the following challenges should be investigated as future perspectives.

- The instantaneous exhaust emissions of a vehicle vary significantly under both laboratory and real-world driving conditions (Bishop et al., 1996b; Mendoza-Villafuerte et al., 2017; Rašić et al., 2017), which is an intrinsic limitation for a half-second snapshot remote sensing measurement.
- Automotive emission standard limits are integrated values of a laboratory test cycle in g/km for light duty vehicles or g/kW-h for heavy duty diesel vehicles (Williams and Minjares, 2016), while remote sensing is only a snapshot measurement in concentration ratios (Q_P) of pollutants over CO_2 (Burgard et al., 2006a). There is no simple comparison with cycle test results. Assumptions are made to convert these ratios to absolute concentrations (ppm or %) or EFs (g/kg fuel, g/L fuel or g/km) (Bishop, 2014; Burgard et al., 2006a; Lau et al., 2012; Zhou et al., 2014). They have to be carefully evaluated, especially for diesel and modern gasoline vehicles with lean combustion technology.
- The accuracy of remote sensing in identifying high-emitting diesel vehicles has not been studied yet. Most previous studies compared the calculated emission concentrations (% or ppm) with the screening cutpoints, which were not suitable for diesel vehicles. The issue of frequent false detection of diesel high-emitters was reported in Hong Kong (Section 4). Future research is needed when using remote sensing for identification of high-emitting diesel vehicles, including more advanced remote sensing system (e.g. better sensitivity and accuracy) and improved method for determining the cutpoints.
- Most screening studies used fixed conservative cutpoints in identifying high-emitting vehicles. This may be inappropriate due to the large variability of on-road driving conditions. Dynamic cutpoints need to be developed for screening programs, which take into account the vehicle speed, acceleration, load etc. This could help increase the screening accuracy for both gasoline and diesel vehicles.
- Recent remote sensing studies had identified a gap in diesel NO_x emissions between the type-approval limits and real-driving emissions (Bishop et al., 2013; Carslaw et al., 2011; Carslaw and Rhys-Tyler, 2013; Chen and Borken-Kleefeld, 2014; Huang et al., 2018; Lau et al., 2012; Pujadas et al., 2017). PEMS, which has an accuracy comparable to laboratory testing and is capable of measuring real-world driving conditions (like remote sensing), could be adopted to understand and address this gap (Hooftman et al., 2018).

6. Conclusions

Remote sensing of on-road vehicle emissions has been critically reviewed based on extensive scientific articles and reports. It can be summarized that remote sensing provides a method to measure various exhaust emissions of a large number of vehicles under real-world driving conditions at a relatively low cost, making it an essential supplement to laboratory emission testing. It also offers very valuable data for assessing and setting the environmental policies. As on-road remote sensing is largely an application of absorption spectroscopy, it is a differential measurement which only determines the concentration ratios of pollutants over CO_2. Assumptions are made to convert these concentration ratios to absolute concentrations and emission factors. Investigations are needed to evaluate these assumptions, especially for diesel and modern gasoline vehicles with lean combustion technology. Caution is required when interpreting the remote sensing data due to its large uncertainty and the nature of high variability in real-world driving conditions. Early remote sensing studies showed that the distribution of on-road vehicle emissions was highly skewed so that typically the dirtiest 10% vehicles were responsible for more than half of the total fleet emissions while the majority of vehicles were clean and only emitted very little emissions. This justified the importance and effectiveness of using remote sensing to screen the high-emitting or clean vehicles for taking part in or exempting them from the I/M programs. However, the accuracy and number of vehicles affected by remote sensing screening programs were highly dependent on the cutpoints. Using fixed conservative cutpoints in absolute concentrations (% or ppm) may be inappropriate, in particular for diesel vehicles. Moreover, frequent false detection of high-emitting diesel vehicles was identified and reported in Hong Kong for the first time. Future work is needed to address these issues and challenges in particular for diesel vehicles due to their different combustion technology compared to gasoline vehicles.

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