Improving our understanding of New Zealand’s vehicle fleet greenhouse gas and harmful emissions using measured emissions data – Stage 1

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An important note for the reader

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Abbreviations and acronyms

AADT	Annual Average Daily Traffic
ADR	Australian Design Rules
CH_4	Methane
CO	Carbon Monoxide
CO_2	Carbon Dioxide
DPF	Diesel Particulate Filter
EDAR	Emission Detection and Reporting
EF	Emission Factor
EU	European Union
GHG	Greenhouse Gas
HDV	Heavy-Duty Vehicle (Gross Vehicle Mass [GMV] greater than 3,500 kg)
HFCs	Hydrofluorocarbons
LCV	Light Commercial Vehicle
LDV	Light-Duty Vehicle
MoT	Ministry of Transport
NESAQ	National Environmental Standard – Air Quality
NIWA	National Institute of Water and Atmospheric Research
NO_x	Oxides of Nitrogen
N_2O	Nitric Oxide
NO_2	Nitrogen Dioxide
OAT	One at a time
ONRC	One Network Road Classification
PAMS	Portable Activity-Monitoring System
PEMS	Portable Emissions Monitoring System
PFCs	Perfluorocarbons
PM	Particulate Matter
$PM_{2.5}$	Particulate Matter with an aerodynamic diameter of less than 2.5 microns
PM_{10}	Particulate Matter with an aerodynamic diameter of less than 10 microns
RI	Relative Importance
RSD	Remote Sensing Device
SCR	Selective Catalytic Reduction
SD	Standard Deviation
SE	Standard Error
SF_6	Sulphur Hexafluoride
SO_2	Sulphur Dioxide
TER	Transport Energy/Emission Research
THC	Total Hydrocarbons
UET	Uncertainty Estimation Tool
US	United States
VEPM	Vehicle Emissions Prediction Model
VFEM	Vehicle Fleet Emissions Model
VKT	Vehicle Kilometres Travelled,
VOC	Volatile Organic Compound
WHO	World Health Organization

Contents

Executive summary

This research project aims to enhance our understanding of the magnitude of, and uncertainty in, estimated vehicle fuel use and pollutant emissions in New Zealand, using currently available real-world data. The objective of this research project is to provide a method that will allow development and improvement in the measurement of New Zealand-specific light- and heavy-vehicle emissions factors in New Zealand's Vehicle Emissions Prediction Model (VEPM). The key tasks of this research project are as follows:

- Develop a method of effectively estimating the emissions and associated uncertainty of light- and heavy-duty vehicles in the New Zealand fleet, including consideration of New Zealand-specific fleet vehicle types, driving speeds and route characteristics and their impacts on real-world fuel consumption and emissions.
- Use the above method to identify and prioritise knowledge gaps in our understanding of real-world vehicle fuel use and pollutant emissions.
- Recommend a monitoring method that will fill the identified knowledge gaps.

The key vehicle impact pollutants considered in the study are nitrogen dioxide, particulate matter with an aerodynamic diameter of less than 2.5 microns (health impacts) and carbon dioxide (greenhouse gas emissions).

The method used involves:

- identifying, collating and analysing real-world measurement data, including international studies, to gain an understanding of the uncertainty contained in real-world emission factors
- identifying and collecting New Zealand vehicle activity data (vehicle kilometres travelled) and road gradient data to combine with emission factors
- running the VEPM at a national scale
- integrating the emission factor uncertainty and VEPM outputs into a database/emissions model, denoted as the Uncertainty Estimation Tool (UET)
- using the UET to undertake an uncertainty and sensitivity analysis to identify and prioritise knowledge gaps.

The UET is one of the key outcomes of this project. In fact, it can be regarded as the core of the project, as it collates and summarises the relevant vehicle emissions and performance data that were investigated during the project. It is the mechanism that provides substantiated answers to the research objectives.

For each of the pollutants, the UET allows us to:

- identify the vehicle classes that have the highest impact on fleet emissions and fleet-averaged emission factors as well as the highest associated level of uncertainty
- attribute the total uncertainty into a small subset of model inputs
- subdivide the high-impact vehicle classes into vehicle emission technology types
- undertake a sensitivity analysis on the results to ensure the findings are robust
- identify target vehicle types which, if monitored, will provide data to fill the identified knowledge gaps.

The study finds that light-duty petrol and diesel vehicles are the vehicle classes with the highest impact on fleet emissions as well as the highest associated level of uncertainty. However, heavy-duty articulated trucks feature as having high impact and high uncertainty for both $PM_{2.5}$ and nitrogen dioxide (NO_2).

With this understanding of the types of vehicles and model inputs needed to improve our understanding of real-world vehicle fuel use and pollutant emissions, we propose a follow-up programme for vehicle emissions monitoring which, if implemented, will provide for ongoing development and improvement in the measurement of New Zealand-specific light- and heavy-vehicle emissions factors. This method will enable Waka Kotahi NZ Transport Agency to target resources to improve the VEPM and the Vehicle Fleet Emissions Model (VFEM) 'where it matters' and in a cost-effective manner.

The recommended programme for vehicle emission monitoring entails a three-pronged approach, using a portable emissions monitoring system, a roadside remote sensing device and a tunnel study. These sets of monitoring data would be analysed to differentiate the emissions of specific vehicle types and sizes, and their emission control technology.

Having completed the project, we have made several recommendations for further work to extend or enhance the findings of this project. The recommendations made include a review of new emission-monitoring methods and suggest useful VEPM updates.

Abstract

This research project aimed to enhance our understanding of the magnitude of, and uncertainty in, estimated vehicle fuel use and pollutant emissions New Zealand, using currently available real-world data. The project developed a method of effectively estimating the emissions of New Zealand's light- and heavy-duty vehicle fleet. The method was then used to identify and prioritise knowledge gaps in our understanding of real-world vehicle fuel use and pollutant emissions.

For each of the pollutants considered in the study, the vehicle classes with the highest impact on fleet emissions as well as the highest level of uncertainty were identified. The total uncertainty within the high-impact vehicle emissions was then attributed to a small subset of model inputs, including vehicle emission technology. A sensitivity analysis was undertaken on the results to ensure the findings were robust. Target vehicle types were pinpointed for monitoring, to provide new data to fill the identified knowledge gaps.

With the understanding of the types of vehicles and model inputs needed to improve our understanding of real-world vehicle fuel use and pollutant emissions, we developed a programme for vehicle emission monitoring which, if implemented, would deliver ongoing development and improvement in the measurement of New Zealand-specific light- and heavy-vehicle emissions factors. This method would enable Waka Kotahi NZ Transport Agency to target resources to improving the Vehicle Emissions Prediction Model (VEPM) and Vehicle Fleet Emissions Model 'where it matters' and in a cost-effective manner.

The recommended programme for vehicle emission monitoring entails a three-pronged approach using a portable emissions monitoring system, a roadside remote sensing device and a tunnel study.

Several recommendations are made for further work to extend or enhance the findings of this project. The recommendations include a review of new emission-monitoring methods and suggestions for useful VEPM updates.

1 Introduction

1.1 Background

The purpose of this research is to investigate the relevance of (magnitude), and uncertainty in, emission factors and fuel consumption for the vehicles that are prevalent in the New Zealand fleet, and to develop a method for identifying and closing prioritised knowledge gaps in this area as much as possible. The study includes consideration of New Zealand-specific fleet vehicle types, driving speeds and route characteristics and their impacts on real-world fuel consumption and emissions.

A recent real-world vehicle emission study undertaken in New Zealand (Kuschel et al., 2019) recommended the investigation of real-world $PM_{2.5}$ emissions from heavy-duty vehicles (HDVs) and the investigation of the impacts on HDV emissions of vehicle type, load, speed and route characteristics. For this current study, Waka Kotahi NZ Transport Agency widened the brief and required that objective consideration be given to both HDVs and light-duty vehicles (LDVs) when identifying the key vehicle types to be considered in any future emission-monitoring programme. The investigation is undertaken using existing data sources, but for the prioritised knowledge gaps, the most cost-effective way(s) to conduct additional vehicle emission measurements are recommended. It is anticipated that the additional data could be used to update New Zealand's Vehicle Emissions Prediction Model (VEPM), which provides emission factors for individual vehicle classes, and the Vehicle Fleet Emissions Model (VFEM), which provides estimates of vehicle kilometres travelled (VKT), fuel use and greenhouse gas (GHG) emissions.

Ultimately, this research project aims to enhance our understanding of the magnitude of, and uncertainty in, estimated vehicle fuel use and pollutant emissions in New Zealand, using currently available real-world data. It will also outline a path forward for a cost-effective programme for vehicle emissions monitoring, aiming to fill the most urgent and relevant data gaps.

1.2 Objective and key project tasks

Waka Kotahi defined the objective of providing a way to develop and improve the measurement of New Zealand-specific light- and heavy-vehicle emissions factors. To achieve this objective, the following key project tasks were undertaken:

a) Collate and analyse real-world measurement data, including international studies.

b) Develop a method of effectively estimating the emissions of light- and heavy-duty vehicles in the New Zealand fleet, including consideration of New Zealand-specific fleet vehicle types, driving speeds and route characteristics and their impacts on real-world fuel consumption and emissions.

c) Use this method to identify and prioritise knowledge gaps in our understanding of real-world vehicle fuel use and pollutant emissions.

d) Make recommendations regarding the vehicle types that should be prioritised for real-world emission measurement, to address gaps in knowledge.

e) Recommend a monitoring method that will fill the knowledge gaps identified.

1.3 Structure of the report

To achieve the objectives of the research, 10 tasks were undertaken and this report has been structured to present the outcomes of each, as follows:

- Chapter 2: Key vehicle impact pollutants
- Chapter 3: Emission model variables that affect the modelling of vehicle emissions and fuel use

- Chapter 4: Vehicle Emissions Prediction Model
- Chapter 5: Uncertainty Estimation Tool
- Chapter 6: Roadway network and vehicle activity data
- Chapter 7: Uncertainty in real-world pollutant emission factors
- Chapter 8: VEPM modifiers
- Chapter 9: Identifying emission and fuel use knowledge gaps
- Chapter 10: Filling emission and fuel use knowledge gaps
- Chapter 11: Summary of key findings and conclusion
- Chapter 12: Recommendations for further work.

2 Key vehicle impact pollutants

A variety of pollutants are discharged from vehicle exhausts. The two highest priority air quality impacts that vehicle emissions have in New Zealand are human health impacts and contribution to GHG emissions. The National Environmental Standard – Air Quality (NESAQ) aims to manage the human health impact of air pollutants and includes particulate matter (PM) with an aerodynamic diameter of less than 10 microns (PM_{10}), carbon monoxide (CO), nitrogen dioxide (NO_2) and sulphur dioxide (SO_2). Based on human health impacts, a current review of the NESAQ is considering the inclusion of PM with an aerodynamic diameter of less than 2.5 microns ($PM_{2.5}$). The GHG emissions discharged by vehicles include carbon dioxide (CO_2), methane (CH_4), nitric oxide (N_2O) and hydrofluorocarbons (HFCs).

Considering the impact of all the health and GHG pollutants was not practical within this project's resources. Therefore, the scope of this study was confined to a limited number of key vehicle impact pollutants. The objective of this chapter is to identify the key vehicle impact pollutants by considering the following three questions:

- What is the current air quality in New Zealand?
- What are the significant air pollutants and how much of these are discharged by vehicles in New Zealand?
- What is the expected long-term trend in emissions (ie increasing, staying the same or decreasing)?

The pollutants that were identified as being most relevant for New Zealand in terms of GHG emissions and health impacts were then used to define the scope of the subsequent tasks in the study.

2.1 Health impacts

The Ministry for the Environment and Statistics New Zealand (Stats NZ) report on the state of the New Zealand environment via a series of reports entitled *New Zealand's Environmental Reporting Series*. The most recent state of New Zealand's air quality was summarised in the report *New Zealand's Environmental Reporting Series – Our Air 2018* (Ministry for the Environment, & Stats NZ, 2018).

2.1.1 Current air quality in New Zealand

The key findings from *Our Air – 2018* on the current air quality issues in New Zealand were as follows:

- A limited number of roadside monitoring sites have sufficient data to assess long-term trends in annual average NO_2 concentrations:
  - Auckland Council has four (Khyber Pass, Penrose, Queen Street and Takapuna), with data over the period 2004 to 2016 showing a slight decrease (0.5–1.6 $\mu g/m^3$ per year) in annual average concentrations and three of these sites recording exceedances of the 1-hour average NO_2 National Environmental Standard. The last exceedance recorded was at Queen Street in 2012.
  - Waikato Regional Council operated a site at Te Rapa Road in 2017, which recorded exceedances of the 1-hour average NO_2 National Environmental Standard.
- Waka Kotahi established a national network of passive NO_2 monitors in 2007. By 2016, 129 roadside sites were monitoring NO_2 across New Zealand. Thirty-four sites have been operating since 2007. The annual reports between 2007 and 2019 from Waka Kotahi's *Ambient Air Quality (Nitrogen Dioxide) Monitoring Programme* (Tonkin and Taylor, 2020) stated the following:
  - Between 2011 and 2019 there was a gradual decline in median annual average NO_2 values.
  - There was a clear trend of improving air quality over the last three years.

- Ten sites had recorded high (> 40 μg/m^3) annual average concentrations.
- Four of these high sites had been investigated, showing three with consistently high concentrations between 2016 and 2019 and one that had decreased over the same period.
- While general PM concentrations were declining across the country over time, for PM_{10}, the NESAQ was exceeded in 35 of the 69 airsheds in which it was monitored (Note: all were urban locations dominated by residential home-heating emissions but vehicle emissions would have also contributed to the total concentration of PM_{10} measured at these sites).
- For $PM_{2.5}$, the World Health Organization (WHO) 24-hour guideline was exceeded in 17 of the 25 airsheds in which $PM_{2.5}$ was monitored (all were urban locations dominated by residential home heating).
- Several monitoring sites across the country exceeded the annual average PM_{10} and $PM_{2.5}$ WHO guidelines.

- The NO_2 concentrations at several sites in the national monitoring network showed that the impact of NO_2 from motor vehicles was an issue that required management. The observed concentrations and trends in NO_2 showed that air quality issues caused by vehicles were reasonably widespread across the country and were persistent over time, with the expected rate of decrease not being observed in the data.
- Unlike some countries (eg the United States [US]) that have significant amounts of volatile organic compounds (VOCs), which promote the conversion of oxides of nitrogen (NO_x) to NO_2, making the management of emissions of NO_x (and VOCs) an important issue, the data showed only low background concentrations of VOCs in New Zealand's ambient air.
- Despite PM concentrations declining across the country over time, particulate pollution remained a key air pollution problem, with regular NESAQ exceedances still occurring. This was expected to be exacerbated when New Zealand's air quality management focus switches from measuring PM_{10} to $PM_{2.5}$.
- In summary, PM_{10}, $PM_{2.5}$ and NO_2 were the top candidates for targeted measurement and management.

2.1.2 Sources of particulate matter and NO_x/NO_2 in New Zealand

The key findings from *Our Air – 2018* on the sources of air pollution in New Zealand were as follows:

- Vehicle emissions were the third-largest source of energy-related PM_{10} and $PM_{2.5}$ emissions, behind residential heating and manufacturing sources. Residential home heating was the largest single source, at 25% of the total PM_{10}; combustion of fuels in all other sections accounted for 21% of the total PM_{10}; and transport accounted for 9% of the total (Metcalfe & Sridhar, 2018).
- On-road vehicle NO_x emissions were the largest source of NO_x in the country (39% of total emissions).
- On-road vehicle NO_x emissions were higher than the next-largest source – manufacturing – by a factor of three.

For the purposes of this study, it was assumed that tailpipe particulate emissions from vehicles were all $PM_{2.5}$, to reflect the assumptions made in the VEPM. The PM_{10} emissions from vehicles were assumed to be the tailpipe $PM_{2.5}$ plus the particulate discharged from brake and tyre wear.

2.1.3 Summary

In summary, the key air quality health impacts seen in New Zealand were from the discharge of PM_{10}, $PM_{2.5}$ and NO_2, with vehicle emissions shown to be a significant source of these pollutants.

Vehicle emissions were the key driver of ambient air quality concentrations of NO_2 in New Zealand. While there was a general decreasing trend in NO_2 concentrations at roadside sites, monitoring at some New Zealand peak impact sites showed persistently high concentrations.

Vehicle emissions were a relatively small contributor to ambient air quality concentrations of PM_{10} and $PM_{2.5}$ in New Zealand. However, because the National Environmental Standard and WHO Guideline values for these contaminants was often exceeded in many airsheds, the management of all sources of PM_{10} and $PM_{2.5}$ (even relatively small ones) is important.

2.2 Greenhouse gases

To fulfil the reporting requirements of the United Nations Framework Convention on Climate Change and the Kyoto Protocol, the Ministry for the Environment (2020) published *New Zealand's Greenhouse Gas Inventory*. This report identified the sources of New Zealand's GHGs and reviewed their trends over time. The GHGs reported in the inventory were CO_2, CH_4, N_2O, HFCs, perfluorocarbons (PFCs) and sulphur hexafluoride (SF_6). Vehicle exhaust gases include large amounts of CO_2 and much smaller amounts of CH_4 and N_2O. While vehicle air-conditioning systems can contain and discharge HFCs and PFCs, only exhaust gases were within the scope of this study.

New Zealand's primary tool for estimating GHGs from road transportation is the VFEM, which provides estimates of VKT, fuel use and GHG emissions.

A review of recent international literature identified the black carbon fraction of particulate emissions as a climate forcer or GHG. It is now widely recognised that black carbon is a short-lived climate pollutant. Although not routinely inventoried, black carbon is important in terms of the conventional and climate pollutant impacts that prominent PM sources, including vehicles, are responsible for. However, the consideration of black carbon emissions was outside the scope of this project.

2.2.1 Sources of greenhouse gases in New Zealand

The key findings of *New Zealand's Greenhouse Gas Inventory 1990–2019* (Ministry for the Environment, 2021) on the sources of GHGs in New Zealand were that in 2018:

- CO_2 and CH_4 emissions (CO_2-equivalent) were the highest of the GHGs considered and were roughly equal at 41% and 43% of the total emissions, respectively
- the energy sector contributed 41% of the CO_2-equivalent total emissions
- vehicle emissions were the largest combustion source of CO_2 (~60% of total) from energy and manufacturing/construction industrial sources
- agriculture contributed 74% of the total (CH_4) CO_2-equivalent emissions
- vehicle emissions of CH_4 were a very minor source of GHGs.

2.2.2 Trends in CO_2

The key findings of the Ministry for the Environment's *Greenhouse Gas Inventory* (Ministry for the Environment, 2021) on the trends in GHGs in New Zealand were that:

- energy sector emissions increased from 25 kt to 35 kt between 1990 and 2018
- emission levels have been steady over the last 10 years
- transport emissions doubled in the period 1990 to 2018.

2.2.3 Summary

The primary impact on GHG emissions from transport is via CO_2 emissions, and emissions from transportation are increasing.

2.3 Key pollutants

Considering the health and GHG impacts of the pollutants discharged from vehicles, the key pollutants used to define the scope of the subsequent tasks in the study were:

- NO_x
- NO_2
- PM_{10}
- $PM_{2.5}$
- CO_2.

3 Emission model variables that affect the modelling of vehicle emissions and fuel use

The key objective of this chapter is to identify the emission model variables that are consistently reported as being most relevant and/or uncertain in emission and fuel use modelling (see Chapter 9). The results from this investigation guided:

- which variables to focus on when identifying the uncertainty in the VEPM (see Chapter 4)
- recommendations regarding future emission and fuel use monitoring (see Chapter 10).

3.1 Literature review of relevant emission model variables

A review of international papers and reports addressing sensitivity analysis and uncertainty assessment in vehicle emission and fuel use modelling was undertaken. It showed that a range of uncertainty and sensitivity analysis methods have been applied to vehicle emission predictions, varying from relatively constrained (eg Andrias et al., 1993; Dey et al., 2019; Kioutsioukis et al., 2004) to complex and comprehensive statistical analyses (eg Kouridis et al., 2010; Super et al., 2020; Wang et al., 2020).

A limited number of studies have conducted a sensitivity analysis to examine the impact of variability in input data on emission predictions and to determine which input is most relevant and should be prioritised regarding data collection. The relevant results are discussed below, in order of year of publication.

Andrias et al. (1993) conducted a basic sensitivity analysis on COPERT 85 and COPERT 90, using sensitivity analysis and error propagation. Although this work is quite old, the following results were relevant to this study:

1. The main input variables affecting uncertainty in total emission estimates of VOCs and fuel consumption were VKT, fleet mix, hot-running emission factors and average trip length. The latter affected the number of cold starts and the average number of trips per day.
2. The uncertainty in emission factors (expressed as the Coefficient of Variability; ie standard deviation [SD]/mean) increased with progressive emission standards, and that uncertainty in fuel consumption factors was significantly less than (about half) the uncertainty in VOC emission factors.
3. The uncertainty in the emission inventory was significantly smaller than the uncertainty in the input variables.
4. The uncertainty at vehicle class level increased substantially due to lack of input data or scarcity in input data.

Kühlwein and Friedrich (2000) used error propagation to assess the uncertainty in transport emission estimates for Germany in 1994 (NO_x and non-methane hydrocarbons). The *Handbook of Emission Factors* was used in the analysis. This is a 'traffic-situation' model, where (hot-running) emission factors (g/km) are determined by a description of a particular traffic situation (eg 'stop-and-go driving', 'free-flow driving'), rather than average speed (Smit et al., 2010). Five input variables were considered for hot-running emissions, namely traffic volume, fleet mix, driving pattern, emission factors and road gradient. For cold-start emissions, variables such as number of starts, emission factors, fleet mix and temperature were considered. The uncertainty in emission factors was quantified by calculating the standard errors for mean dynamometer test values for each vehicle class. It was found that while emission factors were the most important source of uncertainty for hot-running emissions, the others were also significant contributors. For cold-start emissions, emission factors and number of cold starts dominated the uncertainty.

Kioutsioukis et al. (2004) conducted a comprehensive uncertainty and sensitivity analysis using COPERT III to estimate total emissions for Italy in 2000 and 2010. Forty input variables were grouped into four categories and then parameterised through additional algorithm development and definition of statistical distributions of uncertainty. A Monte Carlo interface was built around COPERT to enable the analysis. Due to a lack of data availability, only Limited Dependent Variables were included for the assessment of uncertainty in emission factors. A two-step sensitivity analysis was performed. First, a screening technique was applied to identify non-relevant variables. Meteorological variables were not identified as being influential. Second, the extended Fourier Amplitude Sensitivity Test method was used to allocate the total uncertainty of the annual emission predictions to the input variables. The most influential variables were, in order of importance:

1. VOCs – trip length, emission factor, (urban) speed, annual mileage, fleet mix
2. NO_x – emission factor, fleet mix, annual mileage, trip length, (urban) speed
3. PM – fleet mix, emission factor, trip length, annual mileage, (urban) speed
4. CO_2 – annual mileage, trip length, (urban) speed, driving share.

The uncertainty explained by the three most influential input variables was between 67% and 80%. Some of those inputs were common among most of the various pollutants such as trip length, emission factor, speed and fleet mix. Emission factors were identified as being an increasingly important source of uncertainty for VOCs, NO_x and PM between the years 2000 and 2010.

Smit (2008) examined the impact of VKT, average speed, traffic composition and choice of emission model on NO_x emission predictions for different road types. It was found that uncertainty in emission predictions could be large (up to a factor of about 3.5). Moreover, they were a function of level of congestion, with uncertainty generally increasing with level of congestion. It was concluded that VKT was a particularly important input variable, as errors in VKT were proportionally propagated into emission predictions. For the other inputs, traffic composition was shown to affect NO_x emissions most strongly, followed by average speed and then emission model choice. The results were similar for arterial roads and freeways.

Kouridis et al. (2010) conducted an extensive uncertainty analysis in 2004 for European Union (EU) countries, using the COPERT 4 model in combination with Monte Carlo simulation. The study required software changes to COPERT to enable the study. The study noted the challenge of having incomplete information. For instance, for vehicle population, uncertainty (SD) was quantified for specific vehicle classes by using estimates from only a few different sources (eg Eurostat, ACEA). If information was not available, uncertainty was estimated based on expert judgement. While this work is quite old, it identified relevant influential and less-influential variables. In fact, 51 input variables were reduced to a limited number of variables that had significant uncertainty associated with them:

1. emission factors (hot/cold)
2. vehicle population
3. annual mileage
4. average speed
5. average trip length
6. urban share of passenger cars
7. oxygen/carbon (O/C) ratio of fuels.

They concluded that emission factors drove the uncertainty in emission predictions. In fact, hot-running emission factors influenced most of the variability in emission predictions (about 80%), followed by HDV annual mileage and cold-start emission factors. It is noted that the work quantified hot-running emissions by 10 km/h speed bins. Cold-start emissions were assumed to have coefficients of variation similar to the hot-running emissions. A lognormal distribution was assumed for emission factors. Uncertainty in emission factors was asymmetric because emission factors were, by definition, above zero and typically reflected the occurrence of a low number of high emitters.

Reyna et al. (2015) used the US Environmental Protection Agency MOVES model to examine the impact on emission predictions of variability in driving conditions, vehicle age distribution, climate and roadway gradient across the US. Other factors, such as use of air conditioning, and inspection and maintenance programmes, were not assessed and held constant. It was concluded that all the examined variables were important for GHG and air pollutant emission estimates.

Quiros et al. (2018) examined sources of uncertainty in roadside plume emission detection systems for trucks, using error propagation, including measurement (analyser) uncertainty, uncertainty in measuring vehicle parameters (speed, acceleration, weight), uncertainty in estimating engine power, and uncertainty in vehicle emissions. Vehicle emissions were the largest source of uncertainty; total (combined) uncertainty (SD/mean) for PM and NO_x emission measurement was estimated to be 35% and 42%, respectively.

Super et al. (2020) conducted a Monte Carlo simulation of emission estimation at the regional EU level and reported uncertainties in total emissions (all sources, not only motor vehicles) of 1% for CO_2 and 6% for CO. However, spatial disaggregation to 1 × 1 km-grid cells significantly increased uncertainty, up to 40% for CO_2 and 70% for CO. This showed that the spatial scale of the Waka Kotahi uncertainty estimation tool (eg New Zealand, road types, etc) was an important consideration. Uncertainty was quantified for activity data and emission factors only. Simplifying assumptions were made. For instance, it was assumed that the uncertainty of the variable with the highest uncertainty was indicative of the overall uncertainty of the emissions. In the case of CO, for instance, the CO emission factor uncertainty was used to quantify overall uncertainty. Interestingly, the uncertainty used for road transport activity data and CO_2 emission factors were similar, (about 5–8%).

Dey et al. (2019) used COPERT 5 to examine the impacts of ambient temperature, humidity, average speed, mileage share and trip length on emission predictions of CO, (NM)VOCs, NO_x, $PM_{2.5}$, PM_{10}, N_2O and CO_2 for Ireland. It was clear that model sensitivity to these inputs was highly dependent on the pollutant considered, with CO, (NM)VOCs and N_2O generally being the most sensitive to input variation. The study found that temperature had a significant impact on cold-start emissions (but not hot-running emissions). Relative humidity did not have a significant impact, but it was noted that temperature and relative humidity were correlated. Average speed and mileage share were both important for all pollutants, as was trip length for CO and (NM)VOCs.

Chart-Asa and Gibson (2015) assessed the impact of including variability in road gradient, (hourly) driving conditions and ambient temperature on traffic emission predictions, integrated air quality modelling and subsequent health impact assessment ($PM_{2.5}$) at a local scale. It was concluded that including MOVES emission factor variability into the analysis made the estimated health impact increase by more than a factor of two, indicating that road gradient, driving conditions and ambient temperature (combined) were important.

Other publications were reviewed but provided limited additional information. For instance, Wang et al. (2020) pre-selected variables of interest and focused specifically on uncertainty in emission factors and fleet mix. Kholod et al. (2016) emphasised the need for improved fleet mix and traffic volume data in countries with low-quality or scarce data (this does not apply to New Zealand). Holnicki and Nahorski (2015) simply assumed uncertainty ranges for emissions from road traffic (and other sources) for urban air quality modelling, varying from ±30% to ±50%, depending on the pollutant. Valenzuela et al. (2017) estimated the uncertainty in GHG emission predictions for Colombia's transport sector, using Monte Carlo simulation. Since the study investigated uncertainty in cost efficiency in different scenarios (electric vehicles, hybrid vehicles, improved fuel economy), their results were not directly useful to us. Nevertheless, fuel economy (ie fuel use or CO_2 emission factor) was identified as being one of the most important factors in overall uncertainty

Finally, Tomlin et al. (2016) assessed the impact of uncertainties in 26 model input variables used for local NO_2 dispersion modelling. High-resolution emission modelling was used, thereby capturing variability in traffic volumes and driving conditions. Uncertainty in emission modelling was assessed only for NO_2 direct fraction (% NO_2 in NO_x) and traffic demand. The most influential variables were identified as 'wall roughness length' (high traffic junction, near wall site), (above roof) wind direction and specific NO_x chemistry parameters. Traffic demand and NO_2 direct fraction were shown to be important as well. This work illustrated that in terms of population exposure assessment, which was outside the scope of this project, uncertainty in traffic emission predictions was followed by additional and significant uncertainty in dispersion modelling and atmospheric chemistry processes. The study concluded that overall predicted NO_2 concentrations at the urban sites were uncertain to within approximately a factor of two.

3.2 Summary

In conclusion, the literature review suggested the following:

1. A general lack of information is often stated as being a challenging aspect in uncertainty assessments.
2. Simplifying assumptions often have to be made, adding further uncertainty to the uncertainty assessment (but these are not accounted for, as this additional uncertainty is unknown).
3. Sensitivity and uncertainty both depend on the pollutant considered, where fuel use and CO_2 emissions are significantly less uncertain, as compared with air pollutant emissions.
4. The main input variables that are consistently reported as being most relevant and/or uncertain are VKT and fleet mix (population, annual mileage, share urban/rural/freeway), (hot-running) emission factors, average trip length (number of cold starts), average speed (driving conditions) and road gradient.
5. The ranking of the significance of these variables varies with pollutant, and probably with emission model software version and base year.
6. According to some studies, emission factors are an increasingly important source of uncertainty for air pollutant emission predictions.
7. Overall sensitivity to, and uncertainty in, meteorological variables (ambient temperature, humidity) often, but not always, have a minor impact. Significant temperature impacts are reported for cold-start emissions and have recently been found for hot-running emissions.
8. Sensitivity to, and uncertainty in, fuel quality specification are seldom assessed, but the few studies that have done this work note that specific fuel parameters can be significant (eg O/C ratio).

The literature review shows that the available studies provide general direction as to the most important input variables but do not provide sufficient information to complete VEPM variable selection for the Uncertainty Estimation Tool (UET).

4 Vehicle Emissions Prediction Model

The objective of this chapter is to describe the VEPM. A detailed description of the VEPM is provided in the *Vehicle Emissions Prediction Model (VEPM 6.1) User Guide v4.0* (Waka Kotahi, 2020b). The following overview of the model and its features is a summary of the information provided in the User Guide.

The VEPM is an average-speed model that predicts emission factors for the New Zealand vehicle fleet under typical road, traffic and operating conditions. It provides tailpipe emission factors for NO_x, NO_2, $PM_{2.5}$, particulates from brake and tyre wear (PM_{10}), and CO_2.

The emission factors used for the VEPM are based on the results of a high number of empirical tests, using drive cycles that represent real-life driving conditions, including the consideration of acceleration and deceleration, average speed and periods of idle. In addition to average speed, the VEPM considers the impact of:

- vehicle type
- fuel type
- engine capacity (engine size or engine displacement)
- emission control technology.

The VEPM produces fleet-averaged emission factors for use in air quality assessments.

The general structure for the VEPM model is:

$$E_{ij} = \Sigma\left(E_{ijv\ (v=1\to n)}\left(\frac{VKT_v}{\Sigma VKT_{v\ (v=1\to n)}}\right)\right) \qquad \text{(Equation 4.1)}$$

where E is the emission factor in grams per kilometre (g/km), VKT is the annual distance travelled in kilometres, i is the pollutant of interest, j is the 'situation' (a combination of input factors reflecting the type of vehicle use), and v is the vehicle class. This format accounts for the vehicle population and annual mileage, as defined in Section 5.2 of this report, through the use of a single VKT parameter. This is derived directly from the Ministry of Transport's (MoT's) VFEM tool, which returns an estimated VKT value by vehicle class depending upon the base year of the assessment (between 2001 and 2050).

The emission factor for each vehicle class is then calculated using an equation of the format:

$$E_{ijv} = e_{ijv}\ M_{1,ijv}\ M_{2,ijv} \ldots M_{n,ijv} \qquad \text{(Equation 4.2)}$$

where the emission factor is in terms of g/km and M represents an appropriate modifier, which is generally a dimensionless adjustment factor applied to the emission factor, unless otherwise indicated.

The VEPM formats equations with respective modifiers, which will then form the basis of the UET for each key impact pollutant. These are presented in equations 4.3 to 4.9 below.

The calculation for the non-exhaust PM_{10} emission factor is of the general form:

$$E_{PM_{10}(B+T)} = (e_{PM_{10}(B)} + Ee_{PM_{10}(T)})\_number\ of\ axles \qquad \text{(Equation 4.3)}$$

where $e_{PM(B)}$ is the PM_{10} emission factor in g/km for brake wear and $E_{PM(T)}$ is the emission factor for tyre wear, both as a function of the number of axles a vehicle has. All factors are expressed in terms of PM_{10} as indicated.

The calculation for the exhaust $PM_{2.5}$ emission factor is of the general form:

$$E_{PM2.5,j,v} = e_{hot,PM_{2.5},v} f_{PM_{2.5},v} s(m)_{PM_{2.5},v} g(x)_{PM2.5\ jv} + e_{cold,PM_{2.5},j,v} \quad \text{(Equation 4.4)}$$

where e_{hot} is the hot-running emission factor in g/km, f is the fuel correction factor, $s(m)$ is the degradation (deterioration) factor as a function of estimated mileage, $g(x)$ is the gradient factor as a function of speed (x) and gradient, and e_{cold} is the cold-start emission factor. All factors are expressed in terms of $PM_{2.5}$ as indicated.

Where total PM has been considered in this report, this is an addition of $E_{PM2.5,j,v}$ and $E_{PM_{10}(B+T)}$.

The calculation for the NO_x emission factor is of the general form:

$$E_{NO_x\ jv} = e_{hot,NO_x\ v}\ f_{NO_x\ v}\ s(m)_{NO_x\ jv}\ g(x)_{NO_x\ jv} + e_{cold,NO_x\ jv} \quad \text{(Equation 4.5)}$$

where e_{hot} is the hot-running emission factor in g/km, f is the fuel correction factor, $s(m)$ is the degradation factor as a function of estimated mileage, $g(x)$ is the gradient factor as a function of speed (x) and gradient, and e_{cold} is the cold-start emission factor. All factors are expressed in terms of NO_X as indicated.

The calculation for the NO_2 emission factor is of the general form:

$$E_{NO_2,jv} = e_{NO_x,jv} f_{NO_2} \quad \text{(Equation 4.6)}$$

where $e_{NO_x,v}$ is the emission factor for NO_X as defined above, and $f_{NO_2}$is the NO_2 adjustment factor as a function of the estimated conversion factor. The NO_2 adjustment factor varies with fuel and vehicle type.

The calculation for the CO_2 emission factor is of the general form:

$$E_{CO_2,jv} = FC_{jv}\ \rho_{fuel} CV_{fuel} (CO_2 Emission\ Factor)_{fuel} \quad \text{(Equation 4.7)}$$

where FC_{jv} is the fuel consumption factor in litres per 100 kilometres (L/100 km) calculated using equations 4.4 to 4.7, ρ_{fuel} is the density of the fuel for the respective vehicle class in kilograms per cubic metre (kg/m³), CV_{fuel} is the calorific value for the fuel expressed in megajoules per kilogram (MJ/kg), and the $CO_2 Emission\ Factor$ is the carbon dioxide emission factor for the fuel type in tonnes of carbon dioxide per terajoule (T CO_2/TJ).

The calculation of fuel consumption is of the general form:

$$FC_{j,v} = e_{hot,FC,v}\ f_{FC,v}\ s(m)_{FC,v} + e_{cold,FC,v} \quad \text{(Equation 4.8)}$$

where $E_{hot,FC}$ is the hot fuel consumption emission factor in L/100 km, calculated using equations 4.4 to 4.8, f_{FC} is the fuel correction factor for fuel consumption (based on fuel specifications on a particular input year), and $s(m)$ and E_{cold} are the degradation factor and cold-start emission factor as previously defined.

The calculation energy consumption is of the general form:

$$E_{hot,FC,v} = \frac{e_{hot,EC,v} \times 100}{\rho_{fuel,} \times CV_{fuel,}} \quad \text{(Equation 4.9)}$$

where $E_{hot,EC}$ is the energy consumption factor in MJ/km, ρ_{fuel} is the fuel density in kilograms per litre (kg/L), and CV_{fuel} is the calorific value as defined above, in MJ/kg.

In addition, it should be noted that the VEPM itself has inputs of 1 and 0, which are applied to both the $s(m)$ degradation factors and the cold-start emission factors for each pollutant, where relevant, to allow the user to switch on and off the ability to consider each of these modifiers.

5 Uncertainty Estimation Tool

The objectives of this chapter are to:

- describe the purpose of the Waka Kotahi Uncertainty Estimation Tool (UET)
- describe the structure of the tool
- explain how the tool can contribute to identifying emission and fuel use knowledge gaps (see Chapter 9).

The tool is one of the key outcomes of this project. In fact, it can be regarded as the core of the project, as it collates and summarises the relevant vehicle emissions data investigated during the project, and it is the mechanism that can provide substantiated answers to the research questions. Commonly, the majority of variance in model output is attributable to variability and/or uncertainty in a small subset of inputs. The purpose of the tool is to identify these relevant inputs. This will enable Waka Kotahi to target resources to improving the VEPM 'where it matters' and in a cost-effective manner, rather than spreading resources thinly across improvements in various aspects of the VEPM.

5.1 Sources of uncertainty

There are many sources of uncertainty in relation to vehicle emissions modelling. Uncertainty arises because of limited availability of empirical information and/or imperfections in modelling systems. It can generally be referred to as variance, bias and model formulation, as described below:

- **Variance** refers to the range of aspects and factors that together create variability and uncertainty in vehicle emissions. Variance is due to a combination of true variability (diversity in a population) and uncertainty (reflecting a lack or partial lack of information and knowledge). Examples are variability between vehicles (same situation), variability 'within' vehicles (same situation, repeat measurement), variability in driving and traffic conditions (road gradient, adjacent land use, speed limit, congestion, road type, etc), variability in ambient conditions (ambient temperature, humidity, etc) and uncertainty due to sample size and random errors (eg measurement error). It is noted that several factors are already accounted for in the VEPM, reducing uncertainty in predictions (see VEPM Modifiers in Chapter 8).
- **Bias** refers to systematic errors, including mean (or total) values of a measured quantity such as 'total emissions'. A model that is accurate and has no bias will, on average, produce estimates that correspond to the 'true' value. If a bias is known, then it is possible to correct predictions for this. Quantifying systematic errors is challenging because independent data sets are required. A possible source of bias could be using unrepresentative overseas emissions data to model emissions in New Zealand, not reflecting the unique characteristics of the New Zealand on-road fleet (eg drive cycles, driving conditions, climate, fuel quality, periodic technical inspection or inspection and maintenance programmes, sufficient inclusion of high emitters).
- **Model formulation** refers to the fact that all models are simplifications of reality. Model structure and model algorithms inherently reflect a variety of underlying assumptions, specific empirical data (or lack thereof) and selected modelling techniques (eg multiple linear regression, machine learning methods).

This study aims to quantify the main sources of uncertainty in relation to variance, but not bias and model formulation. Independent and New Zealand-specific data sets, such as tunnel studies, are required to assess bias in VEPM model predictions. It is assumed that the structural form of the VEPM is a reasonably good representation of the real-world system and that a large part of the variability in vehicle emissions is already properly accounted for in the VEPM model structure (eg the spatial-temporal and technology factors mentioned earlier). Assessment of uncertainty in VEPM model formulation is therefore outside the scope of this project. However, it is noted that this could be an area for future investigation.

As noted earlier, the structure of a model is often a key source of uncertainty, simply because models are abstract representations of complex real-world systems. For instance, previous studies have reported that deterministic models like the VEPM could systematically underestimate total emissions, simply because stochastic processes are not simulated. Eggleston (1993) compared an emission inventory that uses Monte Carlo simulation against the common deterministic average-speed approach, concluding that using (non-symmetric) probability distributions for emission factors instead of mean emission factors increased total VOC emission estimates by about 10%. Kioutsioukis et al. (2004) compared the results from a Monte Carlo simulation against a central estimates modelling study, reporting that the Monte Carlo-calculated averages were higher than the central estimates with a difference (over the Monte Carlo mean) of 21.5% for VOC, 6.1% for NO_x, 17.1% for PM and 1.5% for CO_2. Similarly, consideration of average-speed distributions as an emission model input, rather than the single average speeds for each road link, generally increased the total network emissions of CO, HC, NO_x, PM_{10} and CO_2 up to +9%, and even up to +24% at the subnetwork level (urban, rural, motorway) (Smit et al., 2008). Investigation into linked traffic and emission models has also highlighted that uncertainty in predictions can be the result of the lack of perfect representation of traffic and emissions behaviour (eg Sayegh et al., 2017).

Thus, model structure needs to strike a fine balance between purpose, input data availability and complexity. For instance, if limited input data are available for a large complex model, a simpler model could in fact provide predictions that are more accurate, while also offering the benefits of transparency and ease of use. Indeed, a previous study (Smit et al., 2010) found there was no conclusive evidence that vehicle emission models that were more complex systematically performed better in terms of prediction error than models that were less complex.

5.2 Uncertainty Estimation Tool structure

The UET will reflect the key inputs of the VEPM and focus on the key pollutants identified in Chapter 2.

The UET will follow the VEPM structure presented earlier in equation 4.1. Here, *Eij* refers to the total emission estimate of pollutant *i* for a particular 'situation' *j*. 'Situation' is defined with a set of key variables that together govern emissions. An example of a predefined situation is 'average speed = 35 km/h, road gradient = 0%, air conditioning = on, vehicle loading = 80%, and land use = urban'. The predefined situation also requires an estimate of vehicle activity, which will be expressed as (total) VKT to align with the VEPM emission factors (g/km, or rather, g/VKT). *Eijv* refers to the estimated total emission of pollutant *i* for a particular 'situation' *j* and vehicle type *v*.

The benefit of this basic structure is that uncertainty is quantified and propagated at the vehicle class level. This design will provide answers to the research questions. To properly quantify the impacts of uncertainty on *Eijv*, the UET will further detail the emission computation via selected key variables that are used in the VEPM, using equation 4.2. *Eijv* is computed as the product of these key variables. These will include vehicle population (*P*), mean annual mileage (*A*), emission factor (*e*), and several modifiers (*M1–Mn*), as determined by the earlier review of uncertainty analysis studies (see Chapter 3). It is noted that the product of population and mean annual mileage is the same as VKT, which is used in the VEPM. Table 5.1 below shows an example of the basic structure of the UET.

Table 5.1 Basic structure of the UET – Emission inventory part

Emission Inventory			Base year X						
i	j	v	Pijv	Aijv		eijv	M1ijv		Eijv
Substance	Situation	Vehicle class	population	mileage	VKT	emis factor	modifier 1	...	emission
NOx	URB	1a	1,000,000	9,000	9,000	1.0	1.2	...	10,800
NOx	URB	1b	1,200,000	10,000	12,000	1.0	1.3	...	15,600
NOx	URB	1c	800,000	11,000	8,800	2.5	1.4	...	30,800
NOx	URB	2a	9,000	50,000	450	10.0	1.1	...	4,950
NOx	URB	2b	7,000	60,000	420	10.0	1.1	...	4,620
NOx	URB	2c	13,000	80,000	1,040	10.0	1.5	...	15,600
NOx	URB	...	...	...	...	...	...	...	...
								Eij	82,370

5.3 Uncertainty and sensitivity analysis

Different sensitivity analysis methods and different types of uncertainty analysis exist, such as numerical simulation (Monte Carlo) and error propagation (Cullen & Frey, 1999; Karantonis & Weber, 2016; Saltelli et al., 2000). One-at-a-time (OAT) nominal range sensitivity analysis with statistical error propagation appears well suited for the purposes of this study, which aims to quantitatively assess the:

1. uncertainty in vehicle class emission predictions
2. sensitivity of total emission estimates to the (plausible) range of variation in model inputs.

Nominal range sensitivity analysis is applicable to deterministic models and evaluates the effect of model outputs exerted by individually varying only one of the model inputs (ie OAT), while holding all other inputs at constant (mean) values. This means that emission predictions for vehicle class *v* are varied individually, with predictions for other vehicles classes held constant. This way, the relevance and uncertainty can be assessed for each vehicle class, substance and situation.

Statistical error propagation refers to an established method in which combined uncertainty is computed by propagating uncertainty in individual input variables. This method works well as long as certain boundary conditions are met to an acceptable degree (distribution symmetry, independent variables). In practice, it appears that Monte Carlo simulation and error propagation often generate similar results (eg Karantonis & Weber, 2016).

Statistical error propagation is fit for purpose; that is, it apportions both relevance and uncertainty to individual vehicle classes. It will identify vehicle classes that 1) are relevant and 2) contribute significantly to uncertainty in total emission estimation. It also allows for the development of a spreadsheet application UET that is intuitive and relatively easy to expand and update.

The method works as follows. The sensitivity of *Eij* (fleet) to the uncertainty in *Eijv* (vehicle class *v*) will be quantified by varying *Eijv* within a 'plausible (uncertainty) range'. A key task of the project is to:

1. quantify the 'plausible ranges' for all key input variables included in the UET (*VKT*, *e*, *M1–Mn*)
2. compute the 'plausible ranges' in *Eijv*
3. quantify their impact on the output, total emissions *Eij*
4. quantify the sensitivity of the study results to the uncertainty in plausible ranges in emission factors.

Thus, the combined uncertainty in all relevant VEPM variables used in the computation of *Eij* are accounted for.

5.4 Plausible ranges

The plausible range quantifies the level of uncertainty associated with any variable in the UET. Determination of plausible ranges in the key building blocks of the VEPM is an important part of the project, as this will largely drive the answers to the research questions. This is also a challenging task, as quantification of uncertainty means dealing with incomplete information. To the extent possible, plausible ranges will be based on analysis of empirical data and supplemented with information from analysis of overseas literature and models. Expert judgement will be required to fill data gaps.

Given its importance and to ensure consistency, it is important to define the term 'plausible range'. Classical statistical theory provides some guidance. Emission inventories combine averaged or summed values to produce a total (emission) value. Plausible range therefore typically refers to the uncertainty in a mean value.

An example is a vehicle class specific emission factor *Eijv*. We are not interested in the range of individual vehicle emission factors (ie the level of uncertainty for a randomly selected vehicle) but rather, in the range of uncertainty in the average emission factor for all vehicles in a particular vehicle class (the on-road fleet). Average emission factors are generally computed by simply taking the arithmetic mean of a sample; that is, a number of emission tests in a particular situation (eg drive cycle in laboratory testing, part of a journey in portable emissions monitoring system [PEMS] studies) or a selection of test vehicles belonging to the vehicle class of interest. However, these mean emission factors are point estimates. In other words, they are unlikely to hit the exact mean value of the on-road 'population' of vehicles in this class. If a range of plausible values are used instead, there is a good chance that the actual mean value will be captured.

A variety of parametric (ie assumptions about distribution required) and non-parametric (ie distribution-free) methods are available to estimate the uncertainty in mean values. Most straightforward is the parametric analytical solution based on classical statistical theory. The way this works is described next.

Since the emission factor is based on a sample, it provides an estimate of the unknown 'true' (population) emission factor. The sample SD provides an estimate of the uncertainty in the measured values. The standard error of the mean (SE) quantifies how sample variance translates into uncertainty in the mean emission factor. It is computed by dividing the sample SD by the square root of the sample size (n = number of test vehicles). This relationship shows that there is more uncertainty in an individual observation (vehicle emission test) than in the estimated mean emission factor. Even if emissions are variable (which they are) and/or there are significant measurement errors, it is still possible to reduce uncertainty in the estimated mean emission factor by increasing the number of measurements.

The plausible range of values for the mean value is equal to the confidence interval. When we have an average emission factor and an estimate of the standard error, the confidence interval can be computed as follows:

$$CI(1\text{-}\alpha) = Eijv \pm t\alpha/2,(n\text{-}1)\ SE \qquad \text{(Equation 5.1)}$$

Here, the symmetric two-sided 1-α confidence interval CI(1-α) multiplies the standard error with the t-statistic with α/2 probability and n-1 degrees of freedom. The t-statistic considers the reliability of the standard error. Equation 5.1 assumes independent observations, lack of bias and normally distributed measurement errors.

The strength of this analytical method is that for large enough sample sizes (say n > 30), the sampling distribution of the mean is itself a normal distribution, with a mean value equalling the sample mean and a SD equal to SE. This is even true when the underlying data are skewed and not normal (central limit theorem[1]). The approximation works well even for relatively small sample sizes for cases in which the empirical data are continuous, unimodal and symmetric (Cullen & Frey, 1999). If the coefficient of variation (SE/mean) is approximately less than 0.3, then a normal distribution may be a reasonable assumption.

Conventionally, a 95% probability level is used, meaning there is a 95% probability that the confidence interval contains the true value of *Eijv*. That is, we can be roughly 95% confident that we have captured the true mean emission factor.

If only a few emission measurements have been taken, which is often the case for vehicle emission factors, the number of degrees of freedom is small and the t-distribution has a large variance. To reduce the width of the confidence interval, we have to reduce the SE. This can only be done by reducing the SD of the measurements and/or by increasing the sample size. It is noted that while values outside the confidence interval are implausible based on the available data, this does not mean they are impossible.

It is also noted that emission measurements typically show skewed (asymmetric) distributions, which can potentially violate the assumption of normality in the uncertainty of the mean. This is generally not an issue for large data sets but it may create issues for small sample sizes and require other methods to determine a reliable plausible range, such as bootstrap resampling or data transformation. It is worth exploring this further, as the uncertainty in the mean may not be very sensitive to the method used (eg analytical versus bootstrap). For instance, confidence intervals using the *t*-distribution described earlier are relatively robust (insensitive) to slight or moderate departures from normality.

An alternative method to the classic parametric approach can be used in a few cases where sample sizes are very small (ie less than 3) and the upper and lower bounds are well understood. The half uncertainty is computed using three simple steps:

1. The plausible range is calculated: maximum value minus minimum value.
2. The total uncertainty is calculated: plausible range divided by the average value.
3. The half uncertainty is calculated: total uncertainty divided by two.

For example, this can be used for the fuel modification factor when the plausible range is accurately known from fuel quality sampling.

In this report, we refer to this method of calculating half uncertainty as the 'known bounds method'.

5.5 Error propagation

The previous section discussed the plausible range (95% confidence interval) of single variables. When different variables are combined and used in the calculation of a 'derived quantity' (eg total emissions), the situation becomes more complex and a method is needed to quantify the propagation of uncertainties into an overall uncertainty in the 'derived quantity'.

Uncertainty can be propagated through a mathematical model to estimate the error in derived quantities. In error propagation, uncertainty (U) is expressed as half the 95% confidence interval divided by the mean/total and expressed as a percentage. This definition of uncertainty corresponds to commonly used plus or minus value when uncertainties are loosely quoted as ± x%.

[1] The central limit theorem for the sample mean shows that the means will be normally distributed for large samples even if the underlying values are not.

The following two sets of propagation rules are relevant for the UET. These are for variable *w*:

1. Addition: uncertainty in the sum of the quantities:

$$U = SQRT(SUM((w\ Uw)^2))\ /\ ABS(SUM(w)) \qquad \text{(Equation 5.2)}$$

and

2. Multiplication: uncertainty in the product of the quantities:

$$U = SQRT(SUM(Uw^2)) \qquad \text{(Equation 5.3)}$$

The process is shown below in Table 5.2. The blue-shaded cells reflect the results from analysis of empirical data, analysis of overseas literature and models, and expert judgement. The cells with red font show the calculation steps. The calculation produces an estimate of the confidence interval for *Eijv* and estimates the contribution of *Eijv* to uncertainty in the total emission estimate *Eij*.

Table 5.2 UET – error propagation

Red font = uncertainty computation

Input from lit review, data analysis, etc.

Uncertainty								
Substance	Situation	Vehicle class	population	mileage	VKT	emis factor	modifier 1	...
NOx	URB	1a	1%	5%	5%	20%	10%	...
NOx	URB	1b	1%	5%	5%	25%	10%	...
NOx	URB	1c	1%	7%	7%	30%	10%	...
NOx	URB	2a	5%	10%	11%	40%	15%	...
NOx	URB	2b	6%	10%	12%	45%	15%	...
NOx	URB	2c	9%	12%	15%	50%	15%	...
NOx	URB	...	...	...	...	...	...	...

%	g	g	Plausible Range		Uncertainty Contribution
U-Eijv	U-Eijv	U-Eijv^2	LCL Eijv (g)	UCL Eijv (g)	Eijv to Eij (%)
5%	568	322,715	10,232	11,368	1%
8%	1,172	1,372,553	14,428	16,772	4%
11%	3,234	10,458,756	27,566	34,034	29%
20%	965	931,708	3,985	5,915	3%
24%	1,102	1,215,136	3,518	5,722	3%
30%	4,602	21,178,404	10,998	20,202	60%
...	...	...	...	...	...
					100%

uncertainty emission inventory	
%	g
U-Eij	U-Eij
7%	5,956

The UET information is summarised in Table 5.3. It shows the mean relative importance (RI) of each vehicle class, as well as the estimated confidence interval for RI, which reflects the uncertainty in the relevance of a particular vehicle class. The largest range (last column UCL-LCL) indicates which vehicle class is potentially of interest in terms of further testing for the particular pollutant and situation.

Table 5.3 UET – summary

Relative Importance				
RI	LCL RI	UCL RI	RNG RI	UCL - LCL
13%	13%	14%	12.5 - 13.7	1%
19%	18%	20%	17.8 - 20.1	2%
37%	35%	40%	34.8 - 39.8	5%
6%	5%	7%	4.9 - 7.1	2%
6%	4%	7%	4.3 - 6.9	3%
19%	14%	23%	14.1 - 23.2	9%
...	...	...	...	...
100%				

Finally, it is noted that bias is not conventionally included in error propagation, as these methods quantify the (random) variance component in uncertainty. It assumes that known sources of bias are removed prior to error propagation.

Since true emissions are unknown, it is impossible to calculate the accuracy of the VEPM. The error propagation method estimates the precision of the VEPM. It also provides an impression of accuracy, if it can be assumed that the VEPM method represents a reliable picture of reality. However, the VEPM likely still contains unknown and unquantified bias due to a lack of New Zealand-specific emissions data. Overseas studies suggest that bias does exist, even within EU countries (eg Andrias et al., 1993). Bias in UET variables will need to be considered separately. Bias can be detected at emission inventory level with a fuel balance verification and for specific situations with independent emission studies, such as tunnel studies and remote sensing.

5.6 Aligning the Uncertainty Estimation Tool

Notably, for the purposes of meeting the target outcomes of this investigation, the UET contains some exclusions to the original VEPM format that are considered to have low impact or low effect on the main results. The base equations for emission factors presented earlier in Chapter 4 account for the key pollutants in the VEPM and the significant modifiers. These equations are varied slightly from those found in the VEPM in terms of prioritising inclusion of key modifiers while keeping the UET in a simple but still effective format.

The inclusions and exclusions of the UET are presented in Sections 5.6.1 and 5.6.2 below.

5.6.1 Uncertainty Estimation Tool inclusions

The UET for each pollutant, where applicable to that pollutant, includes:

- all relevant modifiers where applicable, unless expressly stated in exclusions
- the ability to turn cold-start on and off, as per the VEPM.

5.6.2 Uncertainty Estimation Tool exclusions

The UET for each pollutant, where applicable to that pollutant, excludes:

- the ability to switch on or off the consideration of degradation
- the calculation of the percentage of vehicles in each vehicle age category without working catalysts
- the calculation of the percentage of diesel vehicles in each vehicle age category without working exhaust gas recirculation or selective catalytic reduction systems.

Adding catalyst age to the UET would significantly increase the number of modifiers for the UET, which as discussed later in Section 8.8, have low impact in terms of sensitivity compared with the emission factors themselves. While future work may choose to include this feature, it is considered that not including it still supplies a snapshot in time for vehicles with working catalysts. In addition, the emission factors uncertainty, including real-life testing, captures some of this variability in the uncertainty applied to these factors.

6 Roadway network and vehicle activity data

For this project, the VEPM model was set up to provide emission factors that could be usefully compared to the real-world emission data used in this study. The base year for the VEPM was set to 2018, to align with the year that the PEMS data was collected in New Zealand. The VEPM fleet composition (vehicle class) and VKT are based on the VFEM and this was used for 2018. This chapter provides detail on the roadway network and vehicle activity data that is used in the VEPM to calculate total fleet emissions.

6.1 Roadway gradient

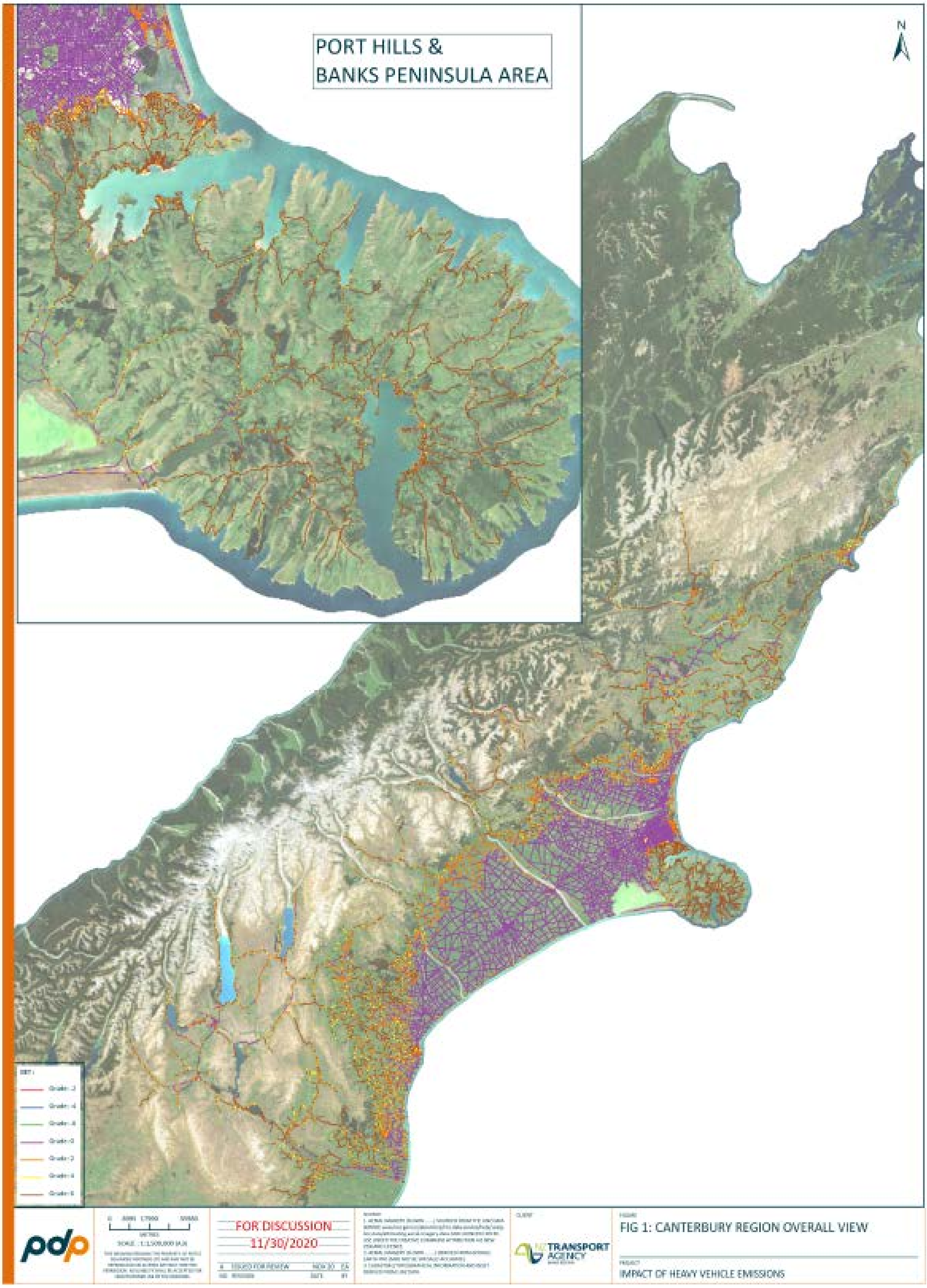
A geo-spatial analysis of the national road network was undertaken for gradient and Annual Average Daily Traffic (AADT). An example of the analysis of the national road network by gradient is shown in Figure 6.1. The breakdown of the national AADT by road gradient is shown in Table 6.1.

Table 6.1 Breakdown of AADT by road gradient

Road gradient	% of total AADT on grade
+ 4.1% to + 6%	6
+ 2.1% to + 4%	4
+ 0.1% to + 2.0%	10
0	60
- 0.1% to - 2.0%	10
- 2.1% to - 4%	4
- 4.1% to - 6%	6

The data shown in Table 6.1 shows that the roads in New Zealand are relatively hilly, with 20% of travel upgrade (positive road gradient) and 20% of travel downgrade (negative road gradient). For this study, the VEPM was set up to incorporate this ratio of road gradients into the calculation of the emission factor (EF).

Figure 6.1 Example of road gradient analysis



6.2 Roadway type

A geo-spatial analysis of the national road network was undertaken for road class as defined by the One Network Road Classification (ONRC) (Waka Kotahi, 2020a). The breakdown of the road network, by ONRC and AADT, is shown in Table 6.2. Each of the ONRC categories have been assigned an assumed average vehicle speed.

Table 6.2 Breakdown of AADT by ONRC and vehicle speed

ONRC category	% AADT on-road category	Assumed average vehicle speed (km/hr)
National strategic	0.02%	100
National	6.98%	100
High volume	18.99%	100
Regional	14.61%	100
Arterial	27.26%	75
Primary collector	17.61%	50
Secondary collector	9.55%	50
Access	3.91%	50
Low volume	1.08%	50

To give a precise absolute estimate of total emissions, the VEPM would have been run for the three speed assumptions classified to each ONRC category and ratio of AADT as shown in Table 6.2. The number of VEPM runs and complexity of analysis required to do this is high.

In an attempt to simplify this analysis, two example scenarios were run in VEPM 6.1 for all vehicle classes: one with variable speed as shown in Table 6.2, and one with a weighted average speed calculated as a proportion of AADT (77 km/hr). The total emissions from these two example scenarios were calculated and compared. A small variation (< 7%) in total emissions was observed between using the eight road categories and a single average speed. However, the difference between the two scenarios across each of the vehicle categories within the VEPM was generally observed to be more or less consistent. Because this study focused on relative difference between vehicle categories, it was assumed that using the simplified weighted average-speed approach was appropriate. For this study, the VEPM was set up with an average vehicle speed of 77 km/hr. It is noted that the UET can be used for a more refined spatial analysis (eg for urban, rural and motorway road types or the eight ONRC road types) in future projects.

It is important to note that the approach detailed above on calculating and using vehicle speed data was valid for this study because a national-scale inventory is being developed. If the spatial scale of the inventory was for a city scale (or smaller), then the average-speed assumption would be unlikely to be valid.

6.3 Annual vehicle kilometres travelled

The VEPM uses estimates of annual VKT for each year of relevance to calculate fleet-weighted emission factors by multiplying emission factors in g/km for each vehicle category by the proportion of VKT. Default VKT data in the VEPM6.1 are from the VFEM3, provided by the MoT.

The MoT provides monitored VKT data for all vehicle categories, with the exception of hybrid and electric vehicles. For use in the UET:

- the MoT monitored VKT data was adopted for vehicle classes for the year of 2018, in place of the VFEM3 VKT values, to reflect real-life monitored VKT values in the fleet-weighted emission factors
- the VFEM3 VKT data breakdown was used when applying the UET to vehicle technology standards, rather than categories that were more aggregated, because the MoT monitoring data did not contain this level of detail.

The data for calculating the total uncertainty for each vehicle category for its fleet VKT contribution are limited. Two sources of VKT data are available from the MoT: the monitored data, and the VFEM3 values for each vehicle category. To estimate VKT for each vehicle category using the limited available data, the half uncertainty for each pollutant, using the known bounds method, was used. The half uncertainty calculated in this manner ranged between 3% and 9%.

This method was then compared with the classic parametric method using the two data points available for 2018 (n = 2), which resulted in a wider range of VKT uncertainty estimates for vehicle classes, ranging from 1% to 27%. This resulted in some uncertainties for vehicle classes being both more and less conservative than the known bounds method.

In this situation, it could not be confirmed whether the MoT or VEFM3 data was likely to represent the lower, middle or upper bounds of the likely VKT range and therefore, the classic parametric method-derived uncertainty was adopted for use, for consistency. To obtain sensible values, this uncertainty could be further refined by obtaining a wider range of data from VKT estimates and models for the year 2018 and estimating the uncertainty again, using the classic parametric or bootstrap resampling methods, which would be more appropriate for use with a sufficient sample size.

7 Uncertainty in real-world pollutant emission factors

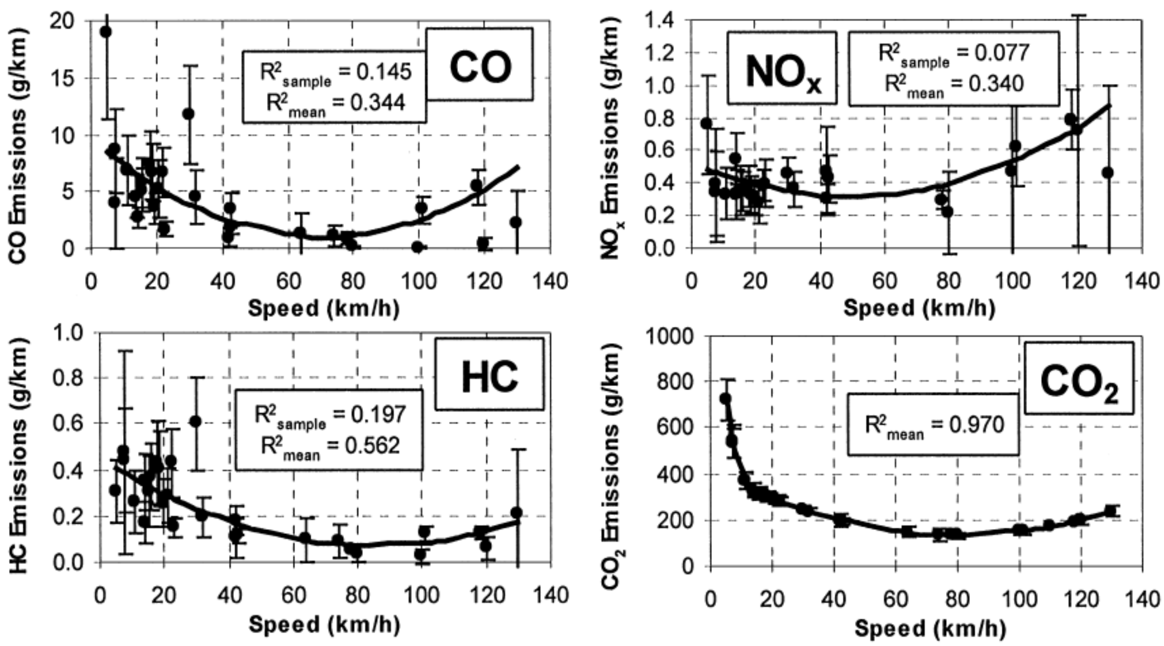
The objective of this chapter is to provide estimates of uncertainty in vehicle emission factors, which will be used to identify emission and fuel use knowledge gaps (see Chapter 9).

7.1 Background

As has been known for a long time, vehicle emission factors have substantial uncertainty (eg see Figure 7.1). The difference between air pollutants and CO_2 is also clear; CO_2 emission factors (and thus fuel consumption rates) have less uncertainty than emission factors for air pollutants.

The wide confidence intervals for air pollutant emission factors are mainly caused by inter-vehicle variability (eg clean vehicles combined with a few high emitters in one sample over a particular real-world drive cycle).

Figure 7.1 COPERT emission factor functions (black line) and average measured values (dots) over real-world drive cycles with 95% confidence intervals for three-way catalyst (TWC) 1.4–2.0 litre petrol passenger cars (reprinted from Ntziachristos & Samaras, 2000, p. 4614)

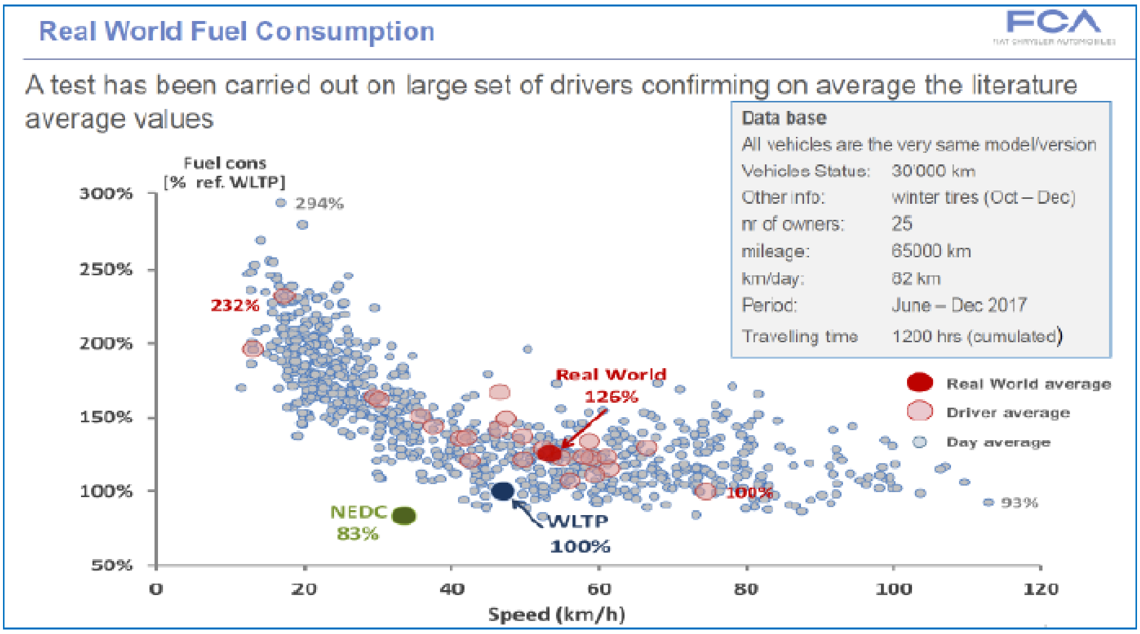


Traditionally, vehicle emission models like COPERT have been largely based on chassis dynamometer emission testing for LDVs and engine dynamometer emission testing for HDVs (Kousoulidou et al., 2010; Smit et al., 2009; Smit et al., 2010). Uncertainty in emission factors depends on the size of the vehicle sample, selected drive cycles, test conditions and test facility (test equipment, operators); for instance, large differences have been observed between emission-testing laboratories (Kioutsioukis et al., 2004).

More recently, on-board emission testing has become the method of choice for vehicle emission measurement. On-road emissions testing with PEMS covers a wide variety of driving conditions and is typically characterised by limited repeatability (Weiss et al., 2011). PEMS testing will add more uncertainty to the emission test results. For instance, Giechaskiel et al. (2018, 2019) noted that 50% to 60% additional uncertainty is regarded as a conservative estimate for PEMS NO_x measurements, as compared with laboratory measurements.

The impact of real-world variability is shown in Figure 7.2. Even for relatively stable fuel consumption, a significant level of variability is obvious in this figure, even though the data were collected for similar vehicles and averaged over the day, as well as over drivers. Daily trip averages ranged significantly from 93% to 294% of the Worldwide Harmonized Light-duty Test Procedure reference value (100%) (Nokes et al., 2019).

Figure 7.2 Variation in real-world fuel consumption data for nominally identical vehicles, driven by 25 different drivers, each carrying out multiple trips (reprinted from Nokes et al., 2019, p. 24)



To quantify uncertainty in VEPM emission factors in this project, a two-pronged approach was used. The first step was to analyse a large database of Australian empirical vehicle emissions data (see Section 7.4). The second step was to collect and review studies that have published real-world emission factors (see Section 7.5). The two steps were then combined to produce defensible plausible ranges for the mean emission factors used in the VEPM.

7.2 Analysis of empirical vehicle emissions data

Comprehensive vehicle emission test programmes were conducted in Australia from the late 1990s until 2009. They enabled the development of Australian vehicle emission models such as COPERT Australia and the P∆P (power-delta-power) emission simulation tool from 2012 onwards.

The test programmes involved chassis dynamometer testing of hundreds of motor vehicles, often with both aggregated ('bag') and modal ('second-by-second') testing for various pollutants and over different (real-world) driving cycles. For instance, the second National In-Service Emissions (NISE2) study (Department of the Environment, 2009; Roads & Traffic Authority, 2009) provided almost 2 million seconds of petrol LDV emissions data for the criteria pollutants and CO_2. Similarly, the South Australian Test and Repair (SATR) programme (Department for Transport, Energy and Infrastructure, 2008) provided almost a million seconds of diesel LDV/HDV emission data for the criteria pollutants PM (Laser-Light Scattering Photometry or LLSP) and CO_2.

The programmes included tests over Australian real-world driving cycles that were developed from on-road driving pattern data in Australian cities. One real-world cycle was developed for petrol LDVs (CUEDC-P) and six (vehicle-class-dependent) real-world cycles were developed for diesel vehicles (CUEDC-Ds). CUEDC stands for 'Composite Urban Emission Drive Cycles' and '-P' or '-D' denotes petrol or diesel (see Figure 7.3 and Figure 7.4). The real-world driving cycles were developed for four distinct traffic situations (congested, residential, arterial and freeway) and different vehicle classes (to properly reflect speed-acceleration characteristics with different power-to-mass ratios), to reflect representative driving behaviour in Australia

Figure 7.3 CUEDC-P drive cycle (reprinted from Transport Energy/Emission Research [TER], 2020a, p. 13)

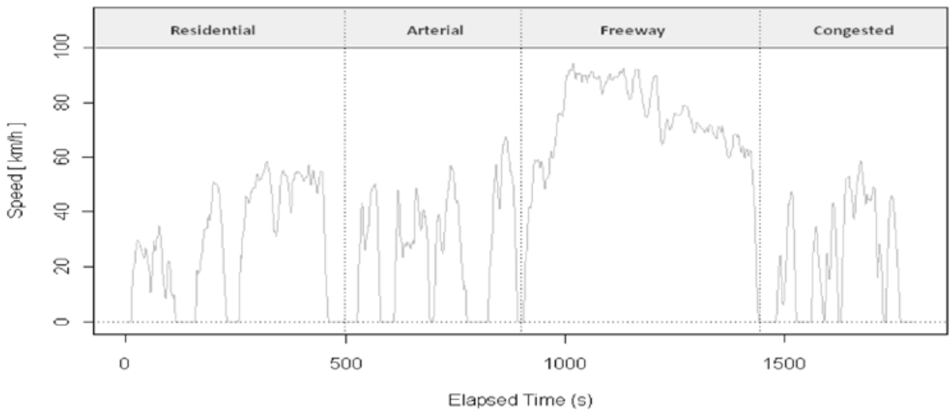
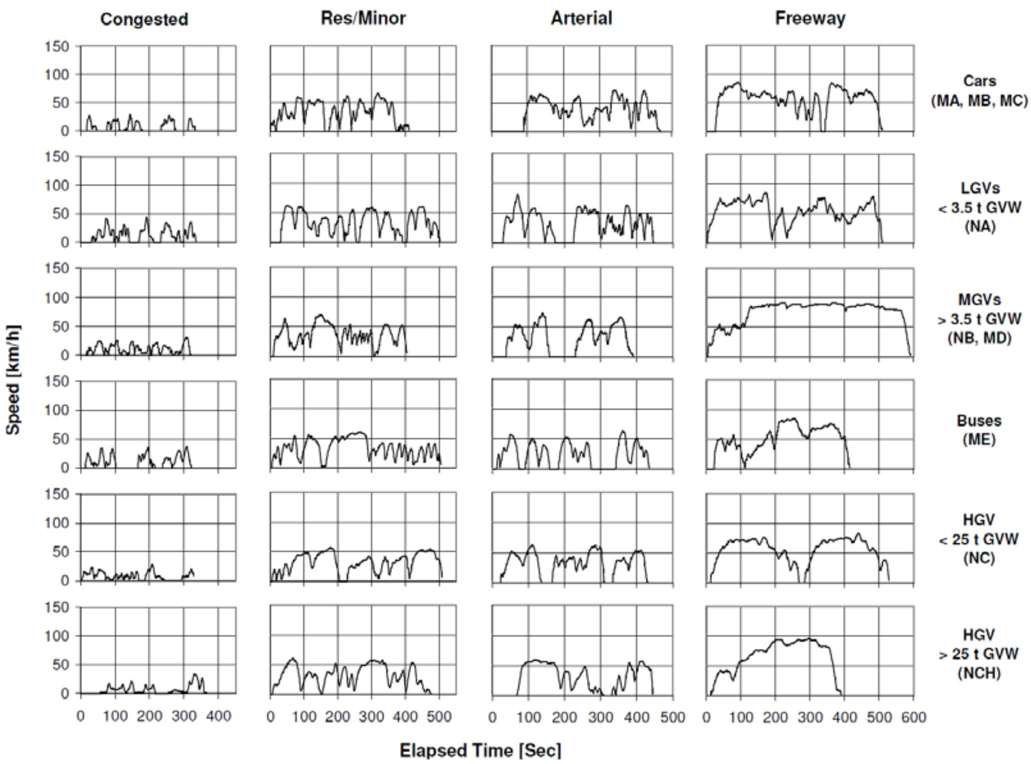


Figure 7.4 CUEDC-D drive cycles (reprinted from TER, 2020a, p. 13)



Empirical emissions data from the various programmes were collated into a single emissions database, after a thorough data-verification and -correction procedure (Smit, 2013). The current TER vehicle emissions database contains 11,894 individual vehicle tests and 1,728 unique test vehicles.

The comprehensive in-service vehicle emission test programmes were conducted until 2009 and underpinned Australian policy design and evaluation work. They arguably surpassed similar programmes in the EU and US in terms of the number of vehicles tested. The only issue is that these programmes have not continued; no significant and publicly available vehicle emission measurement programmes have been conducted in Australia since 2009. Only one Australian PEMS study was conducted by the Australian Automobile Association in 2017 and these data are not publicly available. This means that emissions data are available for LDVs up to Australian Design Rules (ADR)79/01 (E3 for petrol, E4 for diesel) and up to ADR80/00 for HDVs (EIII). Nevertheless, the TER vehicle emissions database is still useful for examining uncertainty in emission factors and identifying possible trends.

7.3 Methods to determine plausible range for emission factors

A variety of parametric (ie assumption about distribution required) and non-parametric (ie distribution-free) methods are available to estimate the uncertainty in mean values. Most straightforward is the parametric analytical approach based on classical statistical theory. When we have an average emission factor *e* and an estimate of the SE (ie SE = stdev(e_x)/sqrt(n), the confidence interval can be computed as follows:

$$CI(1\text{-}\alpha) = e \pm t_{\alpha/2,(n-1)}\, SE \qquad \text{(Equation 7.1)}$$

Here, the symmetric two-sided 1-α confidence interval CI(1-α) multiplies the standard error with the t-statistic with α/2 probability and n-1 degrees of freedom. The t-statistic considers the reliability of the standard error and creates wide confidence intervals for small sample sizes. For instance, for a sample size n = 30, the value of the t-statistic is 2.0, but this increases to 2.1, 2.3, 2.8, 4.3 and 12.7 for n = 15, 10, 5, 3 and 2, respectively.

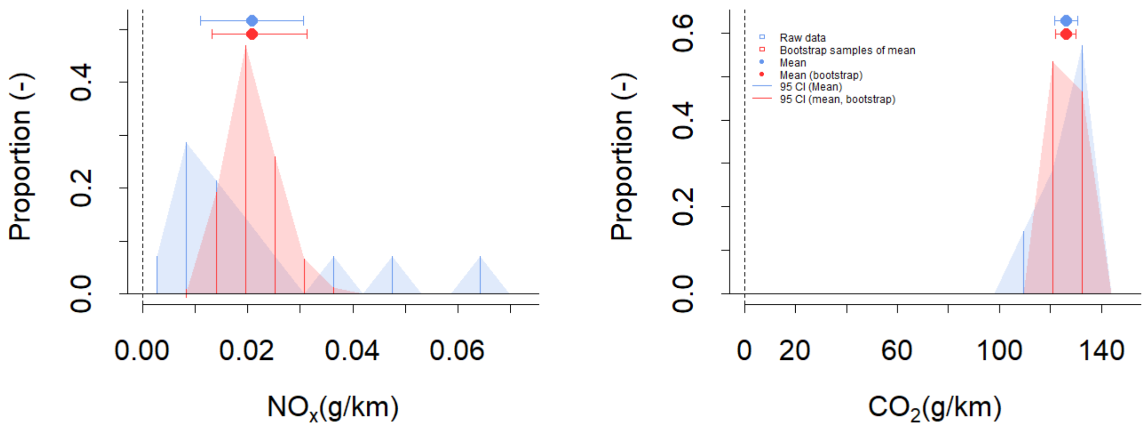
The classical parametric approach assumes independent observations, lack of bias and normally distributed measurement errors. For a significant sample size (n ≥ 30), the sampling distribution of the mean emission factor is a symmetric normal distribution with a mean value equal to the sample mean and a SD equal to the standard error (SE). This is even true when the underlying data is skewed and not normal (central limit theorem).

It becomes trickier for skewed data with small sample sizes, which is often the case for emission factors. Therefore, this section examines the sensitivity of the predicted uncertainty in the mean emission factors to the method used; that is, the classical parametric (analytical) approach versus the non-parametric (bootstrap) approach. The bootstrap approach emulates the process of obtaining new sample sets. The emission factor data are resampled with replacement 1,000 times and the mean emission factor is calculated and stored each time. The result is an approximate sampling distribution for the mean emission factor (n = 1,000), from which the confidence intervals are directly calculated.

It is noted that bootstrap computations are increasingly affected by sampling errors (representativeness) for very small sample sizes. However, the objective here is to examine the impacts of calculation methods on asymmetric emission factor distributions of varying sample size. In this project, a bootstrap simulation was conducted in R to estimate the (grand) means and associated non-symmetric 95% confidence intervals (CI) for the complete TER empirical emission factor database. This was done for 69 vehicle classes, 40 real-world drive cycles and hot-running emissions.

Figure 7.5 shows an example for measured (average) NO_x and CO_2 emission factors for 14 small petrol-driven passenger cars (ADR79/01) on the CUEDC-P real-world drive cycle. Two distributions are shown: the actual measured emission factor distribution (blue) and the bootstrapped mean emission factor distribution (red).

Figure 7.5 Measured (mean) hot-running emission factor distributions for 14 small petrol-driven passenger cars (ADR79/01, Euro 3) on the CUEDC-P real-world drive cycle, including estimated mean emission factors and 95% confidence intervals



The emission factor and bootstrapped mean emission factor distributions are not symmetric, being skewed to the right (NO_x) or left (CO_2). However, it is evident that the mean emission factor distributions are more symmetric than the measured emission factor distributions. The charts also include the mean emission factor as it would conventionally be computed in emission modelling (blue dot at the top; ie arithmetic mean of 14 measured average emission factors) and the bootstrapped mean value (red dot at the top; ie the mean of 1,000 bootstrapped mean values). The confidence intervals are also shown for both methods with horizontal lines at the top of the charts.

The point of interest is the difference in the two computed confidence intervals, or in other words, the plausible range of the mean emission factor for this particular vehicle class. The predicted mean values are the same, but the conventional method is more conservative. For NO_x, both methods predicted a mean emission factor of 29 mg/km, but the bootstrap method predicted a confidence interval of 18 to 42 mg/km, whereas the conventional method predicted a slightly wider interval of 15 to 43 mg/km. For CO_2, both methods predicted a mean emission factor of 152 g/km, but the bootstrap method predicted a confidence interval of 143 to 158 mg/km, whereas the analytical method predicted a slightly wider interval of 143 to 160 mg/km.

Another example is shown in Figure 7.6 for articulated trucks. It is a similar story. The differences in the method used to compute the plausible range in the mean emission factors were small and not of practical significance for this study.

Figure 7.6 Measured (mean) hot-running emission factor distributions for 23 articulated diesel trucks (ADR80/00, Euro III) on the CUEDC-D-NCH real-world drive cycle, including estimated mean emission factors and 95% confidence intervals

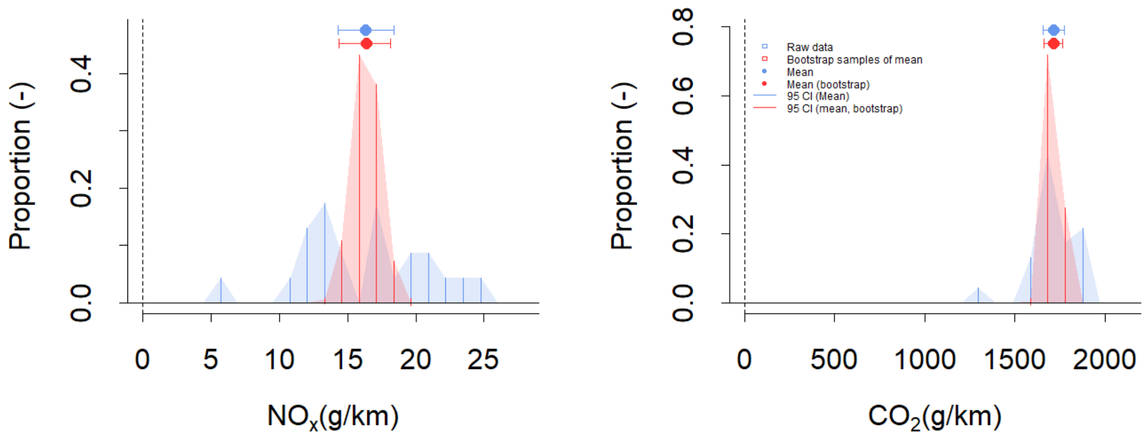


Figure 7.7 summarises the results for the entire TER emission factor database. The plots show the estimated uncertainty half range of the mean emission factor with the two methods for 477 model classes. A 'model class' is defined as a particular combination of vehicle type, fuel type, technology type (ADR), drive cycle and driving mode. Sample size varies from 4 to 43 and dot size (surface area) reflects the sample size for a particular model class. The 'uncertainty half range' is expressed as a percentage and refers to half the 95% confidence interval or half the plausible range divided by the mean value. For the classical parametric approach, this is the difference between the mean emission factor and the upper or lower 95% confidence limit, divided by the mean emission factor. Since the analytical approach assumed a symmetric distribution, it did not matter whether the upper or lower confidence limit was used. For the asymmetric bootstrap estimates, the maximum difference between the mean emission factor and the upper or lower 95% confidence limit was used.

Figure 7.7 Estimated uncertainty half range (% of mean) using two methods (analytical, bootstrap) for three pollutants (dot size reflects sample size)

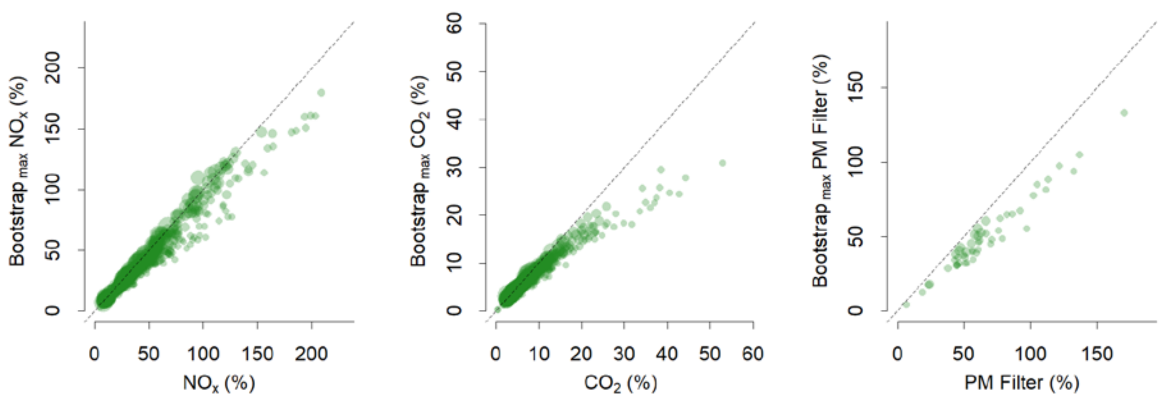


Figure 7.7 shows that the classical parametric method generally led to more conservative estimates of plausible (half) range than the bootstrap method. The percent difference between the bootstrap and conventional method was approximately −45% to +15% for NO_x, −45% to +10% for CO_2 and −45% to −10% for PM.

In conclusion, although vehicle emission factors are usually based on skewed emission distributions and small sample sizes, the conventional analytical approach to estimating 95% confidence intervals provides a reasonable approach for determining plausible ranges in average emission factors. This is useful when raw emissions data are not available (ie data extracted from the scientific literature) and where bootstrap resampling cannot be applied. When raw emissions data are available (see the next section), the maximum predicted uncertainty with either the parametric or bootstrap approach is used.

7.4 Uncertainty in Australian emission factors

The next step in this project was to interrogate the TER database and quantify the plausible range in hot-running mean emission factors for different vehicle classes and real-world drive cycles.

To account for differences in emission factors between countries due to varying sulphur content of the fuel (particularly diesel), the TER diesel emissions database was normalised to a common sulphur content, basically converting the PM emission results of older test programmes to reflect ULSD (< 10 ppm S). Petrol vehicle emissions were not further corrected and reflect Australian fuel quality at the time of measurement.

Possible relationships between the absolute average emission factor and level of uncertainty were examined. The absolute emission factor was used as it provided a direct link with VEPM emission factors. Figure 7.8 shows the results for nine vehicle types: petrol passenger car (CAR_P), diesel passenger car (CAR_D), petrol SUV (SUV_P), diesel SUV (SUV_D), petrol light commercial vehicle (LCV_P), diesel light commercial vehicle (LCV_D), diesel bus (BUS_D), diesel rigid truck (RTR_D) and diesel articulated truck (ATR_D).

Many variables influence absolute emission factors, such as vehicle engine and emission control technology, emission standard, driving conditions, tampering with engines or emission control systems, ambient conditions and test conditions. These variables were inherently considered and reflected in the absolute emission factors used on the x-axis of the following figures. Because of real-world complexity in terms of influencing factors and the need for robust relationships, absolute emission factors were assumed to collectively reflect influencing factors in a useful way. In other words, it was assumed that it did not significantly matter, in terms of uncertainty, whether a high emission factor was related to congested driving conditions or older technology; that is, the level of uncertainty associated with the measured mean emission rate was expected to be approximately the same. Of course, once more PEMS data becomes available, it will be possible to further expand the approach and develop uncertainty–emission factor relationships for different road types and a finer vehicle classification.

Sample size is an important factor in determining the level of uncertainty in an average emission factor. A complication is that sample sizes are unknown for VEPM emission factors. They will be dependent on vehicle class, pollutant, driving mode and traffic situation, and reflect the test data available at the time when the emission factor algorithms were developed. In addition, (hot-running) VEPM emission factors do not directly reflect averaged measurement results, but are fitted regression functions to averaged measurement results for different drive cycles. Therefore, it was not possible in this project to make reliable statements about sample size, and assessing the uncertainty in emission algorithms would have required access to the original test data used.

To move forward, it was assumed that the VEPM emission factors were based on a minimum of three vehicle tests. Therefore, Figure 7.8 shows the hot-running results for real-world drive cycles with a sample size of three or more. The maximum estimated uncertainty was used, either by the classical parametric approach (blue dots) or the bootstrap approach (red dots). Grey linear trend lines have been added (including shaded 95% confidence intervals) to provide a visual guide for possible trends.

Figure 7.8 can be used to estimate plausible ranges for VEPM emission factors by identifying the corresponding vehicle class and mean VEPM emission factor. A relationship between uncertainty and the absolute value of the mean emission factor can be observed. For instance, articulated trucks have high NO_x emission factors exceeding 20 g/km and the lowest level of relative uncertainty. When petrol car NO_x emission factors are below 0.5 g/km, relative uncertainty can become high and exceed 150%.

Figure 7.8 Uncertainty half range in the mean hot-running NO_x emission factors for nine vehicle classes (dot size reflects sample size)

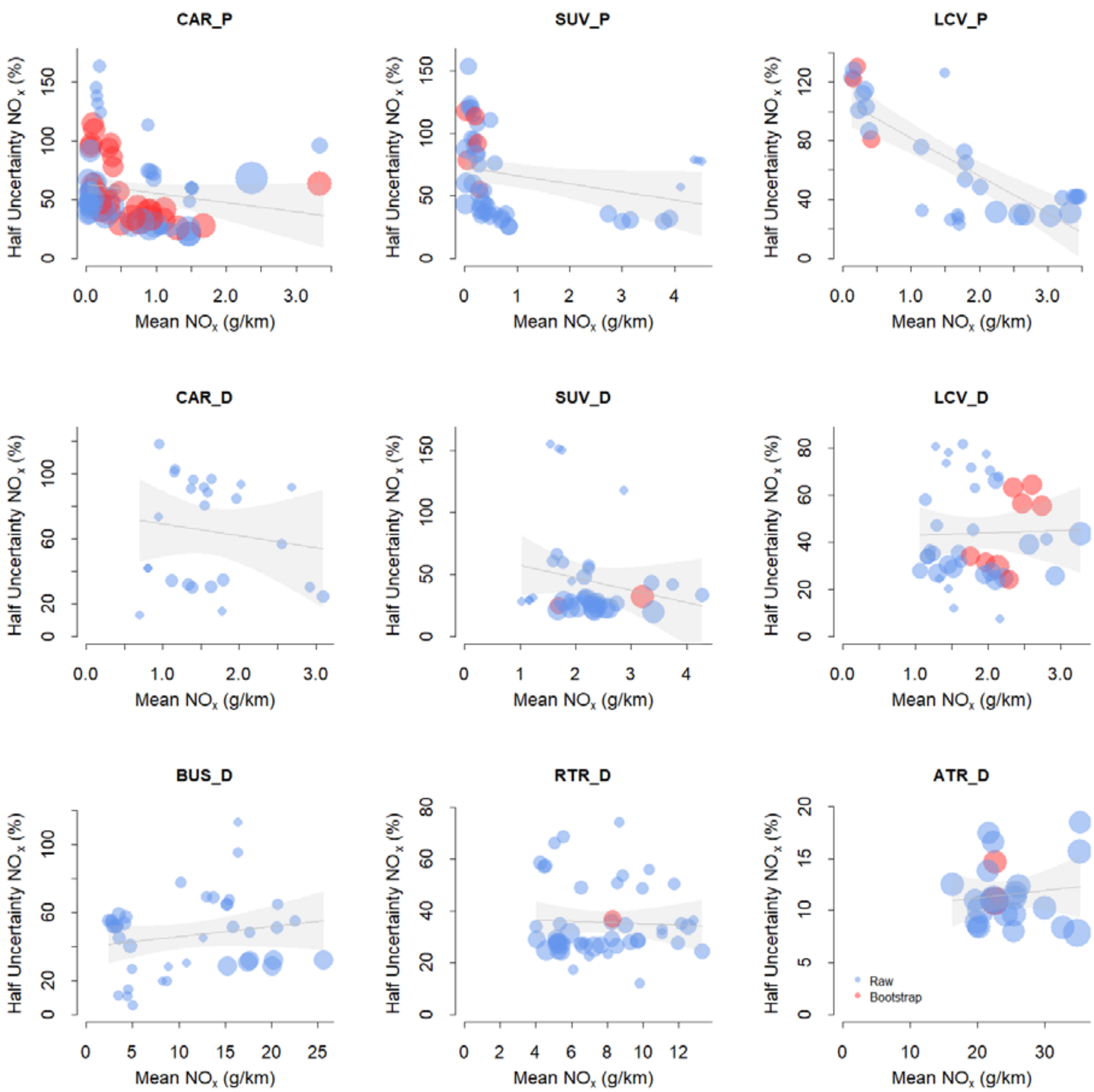
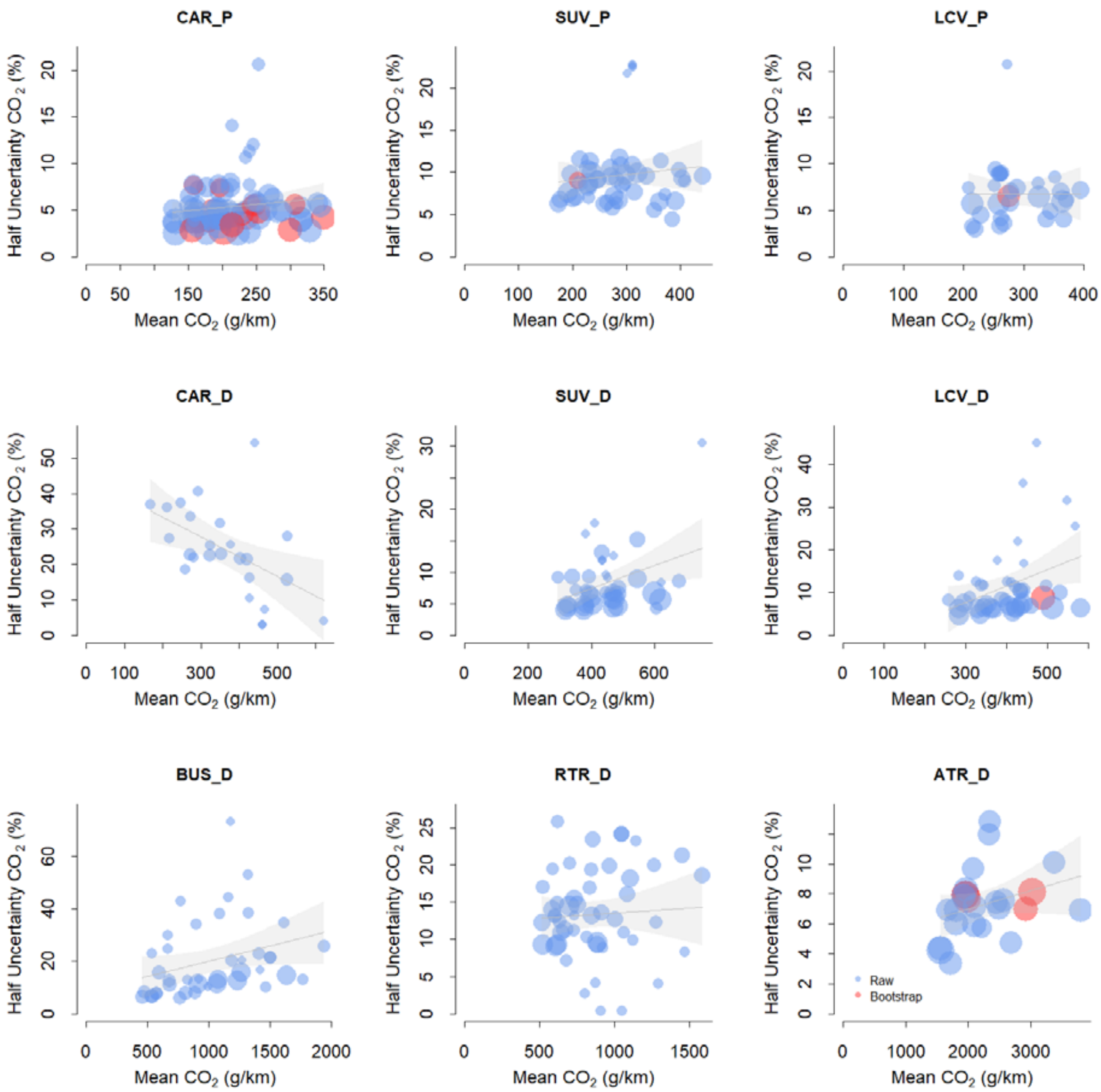


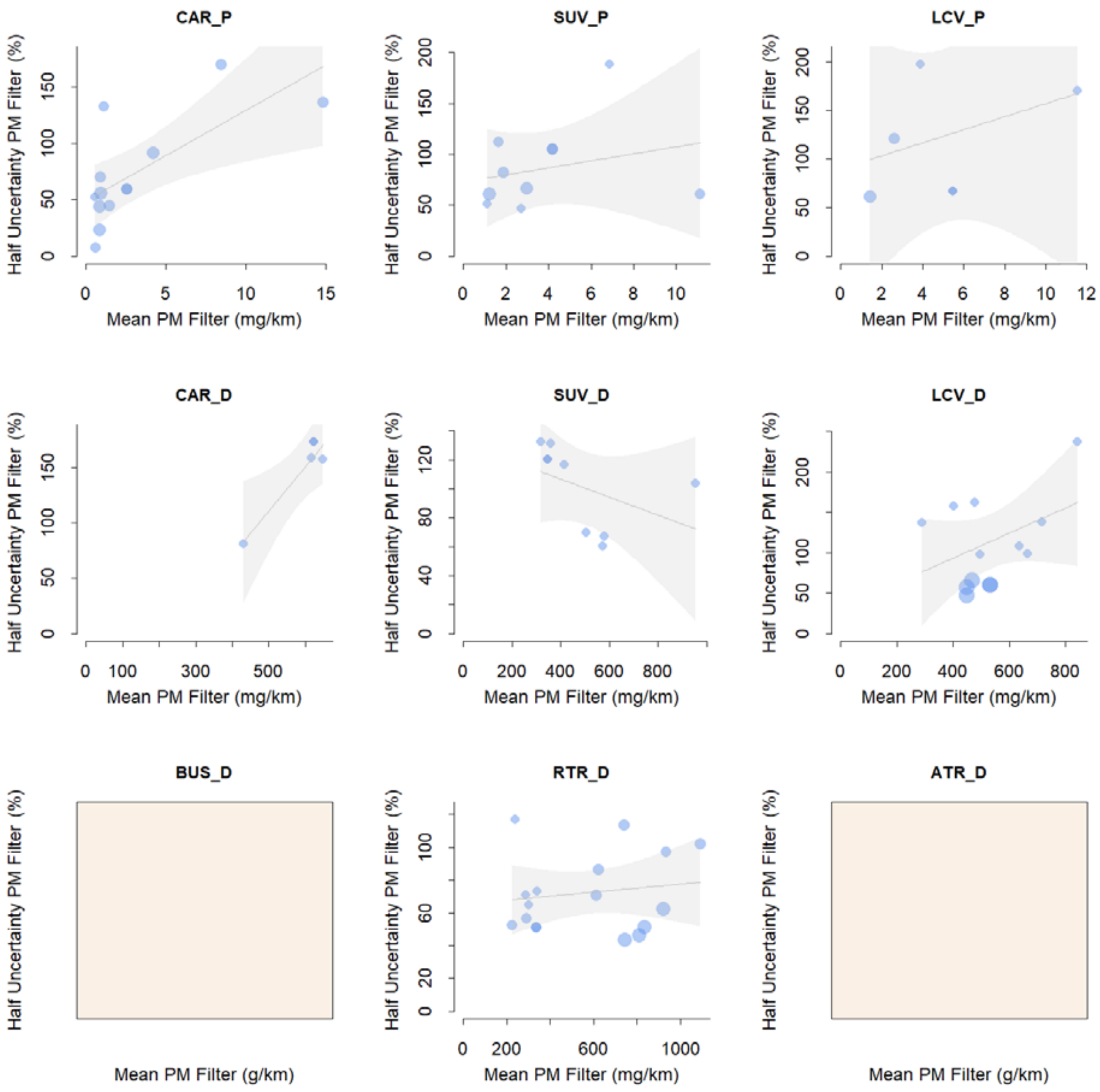
Figure 7.9 shows the results for CO_2. Relative uncertainties are significantly lower than NO_x, generally in the order of 5% to 15%, and generally stable; that is, there generally appears to be no obvious trend with absolute emission factor values, with the exception of diesel cars (CAR_D).

Figure 7.9 Uncertainty half range in the mean hot-running CO_2 emission factors for nine vehicle classes (dot size reflects sample size)



Finally, Figure 7.10 shows the results for PM (filter based). The available measured data for PM (exhaust) emission factors was more limited, even missing for certain vehicle categories. The limited data suggests a high relative uncertainty for PM emission factors for petrol-fuelled vehicles (~50–200%) and a substantial to large relative uncertainty for diesel-fuelled vehicles (50–150%).

Figure 7.10 Uncertainty half range in the mean hot-running PM (exhaust) emission factors for nine vehicle classes (dot size reflects sample size)



7.5 Uncertainty in published real-world emission factors

A vast number of studies have been published to report on vehicle emission factors. It was not feasible to extract and analyse emission factors from these studies within the available budget. Instead, the scientific literature was scanned for LDV and HDV emission factors, with a focus on real-world on-board emission testing (PEMS). The real-world studies reflected a diversity of factors such as driving conditions, topological characteristics (road gradient), meteorological/climate conditions, vehicle emission standards and fuel quality requirements. For this study, this was considered a benefit, as the variability and uncertainty in emission factors was inherently included. It is likely that PEMS data could provide estimates of uncertainty in emission factors that are more conservative than conventional methods such as laboratory emissions testing.

Publications with emission factor data were considered for the uncertainty analysis if 1) they included quantitative uncertainty information; 2) emission factors were expressed in VEPM units (g/km); and 3) data (preferably) reflected real-world on-board testing. Regarding the first point, the studies presented the information in the following three different ways:

1. emission factors for two or more individual vehicle(s), belonging to a particular vehicle class, including the average, SD and sample size of repeat measurements (Grigoratos et al., 2019; Thompson et al., 2014)
2. emission factors for a single vehicle representing a particular vehicle class, including the average, SD and sample size of repeat measurements (Daham et al., 2009; Hadavi et al., 2012)
3. emission factors for a particular vehicle class, including the SD and sample size (ie number of vehicles tested) of repeat measurements (De Vlieger et al., 1997; Gierczak et al., 2007; O'Driscoll et al., 2016; Valverde et al., 2019; Weiss et al., 2011; Weiss et al., 2012).

Generally, both between-vehicle and within-vehicle variability in emissions is important. Variability in laboratory-based emission factors is usually dominated by between-vehicle variability, since test conditions are controlled. Recent on-road studies have arrived at a different conclusion. For instance, Papadopoulos et al. (2020) analysed variability in emission measurements of Euro IV and V diesel trucks and concluded that the within-vehicle variance due to driving conditions (speed, road slope, etc) and randomness appeared to be the most important component of the emission factor variability.

It is therefore important to reflect both between-vehicle and within-vehicle variability in the estimation of uncertainty. For determination of plausible uncertainty ranges in emission factors, option 1 above is considered the best, as it allows for assessment of uncertainty in emission factors in terms of both between-vehicle and within-vehicle variability. Within-vehicle variability is of particular interest for PEMS data because variability in test conditions may be a significant additional source of uncertainty, in comparison with laboratory-controlled emission tests. Option 2 above quantifies only the within-vehicle variability in emission factors, whereas option 3 quantifies only the between-vehicle variability.

Surprisingly, there was only limited data available in the required format of options 1 to 3 in the published scientific literature. Most studies presented mean emission factors without the additional information relevant to uncertainty (SD, sample size, standard error, confidence limits, coefficient of variation), or showed emission factors with or without confidence intervals in charts, but not in an extractable format (tables). Some studies presented average emission factors and only included a high-level comment regarding uncertainty. For instance, Quiros et al. (2016) presented HDV emission factors (four vehicles) and stated the SE was commonly 40% or more because of the variable on-road driving conditions.

A future option could be to contact authors requesting the raw data or additional uncertainty information, and then when that is received, to process the data and reconduct the analysis; however, this would be time consuming and it was beyond the scope of this current project. The best way forward in the future may be to analyse raw (PEMS) emissions data – access to these data could be considered at a later stage.

After reviewing and identifying the useful publications, an emission factor database was created with relevant information, such as study, study type (option 1, 2 or 3), country, vehicle class (type, fuel, emission standard), vehicle (class) ID, pollutant, mode (hot, cold, or both), journey gradient description, journey driving conditions, mean, SD and sample size.

The New Zealand PEMS data were then added. The New Zealand PEMS data allowed for computation of option 3 (between-vehicle variability), since most vehicles were tested once. Three out of 28 vehicles had repeat measurements (n = 2, 3), but these vehicles belonged to different vehicle classes, so option 1 could not be used. The New Zealand PEMS data were classified using vehicle type (PC, SUV, LCV, HDV), fuel type (diesel, petrol), Euro standard and import status (new, used).

The data were subsequently processed in R to compute (grand) mean emission factor values, the associated 95% confidence interval and uncertainty (expressed as % of the mean; ie half the plausible range). For options 2 and 3, the confidence intervals were calculated using the conventional parametric method discussed earlier. For option 1, a statistical random-effects meta-analysis approach was initially used (Deeks et al., 2019). The benefit of this approach was that the impacts of between-vehicle and within-vehicle variance were both quantified.

The aim of meta-analysis is to analyse and integrate the findings of a collection of individual studies. In this context, a vehicle tested over various real-world driving conditions is considered an individual 'study'. The basic data required for the analysis is an estimate of the 'intervention effect' (ie mean emission factor) and the standard error for each study (using SD and sample size for the measured emission factors). A random-effects model considers both within-vehicle and between-vehicle variance and provides an average 'summary' or 'global' effect. This is the (weighted) mean of the measured emission factors for various vehicles in different driving conditions, as well as the associated confidence interval. In the random-effects analysis, each vehicle test is weighted by the inverse of its variance. Since precision is often driven primarily by sample size, the test results are effectively weighted by sample size.

In the PEMS emission factor database, sample size does sometimes vary for individual vehicles (Thompson et al., 2014), which supports the use of the random-effects meta-analysis approach. However, this is not always the case (Grigoratos et al., 2019). When sample size is the same for each vehicle, variance in emission factors will be due to a mix of factors other than sample size (eg technology, age, driving behaviour, etc). Consequently, the conventional parametric approach used for options 2 and 3 is likely more appropriate than variance-weighted results (mean, uncertainty).

Both options 1 and 3 were compared for the two studies, showing that they tended to give different results in the estimate of the mean emission factor value (weighted versus unweighted) and its associated uncertainty. However, there was no consistent pattern by which one method, for instance, predicted systematically higher or lower uncertainty results, although meta-analysis appeared to produce less-extreme uncertainty estimates in some cases. For consistency, the conventional parametric approach (option 3) was used for the two 'option 1 studies', also because this aligned with the method used for the New Zealand PEMS data.

Generally, the conventional parametric approach used to predict confidence intervals assumes that data are (approximately) normally distributed. If the distribution is asymmetrical, then the data are said to be skewed. The skewness of emission test results was checked for this project. In case a significant departure from symmetry was detected, an asymmetric confidence interval was computed, based on the estimated geometric mean and geometric SD. This was required because confidence intervals are approximately symmetric for small ranges of uncertainty (half range of less than approximately 50%) and are positively skewed for large ranges of uncertainty for non-negative variables like emission factors.

The on-road PEMS results for hot-running NO_x emission factors are shown in Table 7.1. It is clear in Table 7.1 that the computed uncertainty can be very large, up to almost 600%. However, large values are almost exclusively associated with a small sample size (n = 2, 3) where large t-statistic values inflate uncertainty estimates, as discussed earlier. In line with the previous sections, a minimum of three vehicle tests was required for inclusion.

Table 7.1 Analysis of published real-world (PEMS) hot-running NO_x emission factors

Vehicle Class	Country	Traffic situation (Road Gradient)	Study Type	Mean EF (g/km)	Sample size	Uncertainty (%)	Reference
PC-P E_1	EU	urban (unknown)	3	0.24	6	77%	De Vlieger 1997
PC-P E_1	EU	rural (unknown)	3	0.17	6	81%	De Vlieger 1997
PC-P E_1	EU	freeway (unknown)	3	0.14	6	75%	De Vlieger 1997
PC-P E_0	UK	urban (none)	2	1.20	3	70%	Daham 2009
PC-P E_1	UK	urban (none)	2	0.89	3	36%	Daham 2009
PC-P E_2	UK	urban (none)	2	0.53	3	70%	Daham 2009
PC-P E_3	UK	urban (none)	2	0.47	3	122%	Daham 2009
PC-P E_4	UK	urban (none)	2	0.65	3	42%	Daham 2009
HDV-D E_III	US	urban (none)	3	2.80	15	10%	Gierczak 2007
LCV-D E_3	UK	urban-rural (unknown)	2	1.86	3	76%	Hadavi 2012
PC-D US_Tier 2	US	urban (variable)	3	0.57	3	112%	Thompson 2014
PC-D US_Tier 2	US	highway (variable)	3	0.48	2	358%	Thompson 2014
PC-D US_Tier 2	US	hilly (variable)	3	0.86	3	165%	Thompson 2014
PC-D E_6	UK	urban (flat)	3	0.43	39	32%	O'Driscoll 2016
PC-D E_6	UK	motorway (flat)	3	0.31	39	39%	O'Driscoll 2016
HDV-D E_VI	EU	low speed (variable)	3	2.91	5	89%	Grigoratos 2019
HDV-D E_VI	EU	medium speed (variable)	3	0.49	5	96%	Grigoratos 2019
HDV-D E_VI	EU	high speed (variable)	3	0.24	5	128%	Grigoratos 2019
HDV-D E_1_used	NZ	low speed - urban (variable)	3	5.28	3	34%	NZ 2019
HDV-D E_1_used	NZ	medium speed - motorway (variable)	3	3.28	2	37%	NZ 2019
HDV-D E_1_used	NZ	medium speed - rural (variable)	3	2.77	2	102%	NZ 2019
HDV-D E_2_new	NZ	low speed - urban (variable)	3	2.79	4	17%	NZ 2019
HDV-D E_2_new	NZ	high speed - motorway (variable)	3	1.38	4	21%	NZ 2019
HDV-D E_2_new	NZ	medium speed - rural (variable)	3	1.18	4	65%	NZ 2019
HDV-D E_V_new	NZ	low speed - urban (variable)	3	5.20	2	64%	NZ 2019
HDV-D E_V_new	NZ	high speed - motorway (variable)	3	3.67	2	19%	NZ 2019
HDV-D E_V_new	NZ	medium speed - rural (variable)	3	4.55	2	22%	NZ 2019
SUV-D E_1_used	NZ	low speed - urban (variable)	3	5.13	2	331%	NZ 2019
SUV-D E_1_used	NZ	high speed - motorway (variable)	3	4.66	2	91%	NZ 2019
SUV-D E_1_used	NZ	medium speed - rural (variable)	3	2.54	2	594%	NZ 2019
SUV-D E_4_new	NZ	low speed - urban (variable)	3	2.50	3	21%	NZ 2019
SUV-D E_4_new	NZ	high speed - motorway (variable)	3	1.41	2	13%	NZ 2019
SUV-D E_4_new	NZ	medium speed - rural (variable)	3	0.68	3	88%	NZ 2019
SUV-P E_3_new	NZ	low speed - urban (variable)	3	0.21	2	312%	NZ 2019
SUV-P E_3_new	NZ	medium speed - rural (variable)	3	0.18	2	193%	NZ 2019
LCV-D E_4_new	NZ	low speed - urban (variable)	3	2.06	3	98%	NZ 2019
LCV-D E_4_new	NZ	medium speed - motorway (variable)	3	1.20	2	28%	NZ 2019
LCV-D E_4_new	NZ	medium speed - rural (variable)	3	0.81	3	107%	NZ 2019
LCV-D E_5_new	NZ	low speed - urban (variable)	3	1.28	2	200%	NZ 2019
LCV-D E_5_new	NZ	high speed - motorway (variable)	3	0.84	2	21%	NZ 2019
LCV-D E_5_new	NZ	medium speed - rural (variable)	3	0.88	2	508%	NZ 2019

Emission factors and uncertainty estimates ($n \geq 3$) are shown in Figure 7.11, which combines the New Zealand and internationally published PEMS data with the analysis of the Australian emissions database (shown earlier in Figure 7.8).

Figure 7.11 Uncertainty half range in the mean hot-running NO_x emission factors for nine vehicle classes (dot size reflects sample size) – blue/red dots = Australian laboratory data (classical parametric/bootstrap); black dots = New Zealand PEMS data (study type 3); yellow dots = PEMS data (within-vehicle variance only, study type 2); green dots = PEMS data (between-vehicle variance only, study type 3)

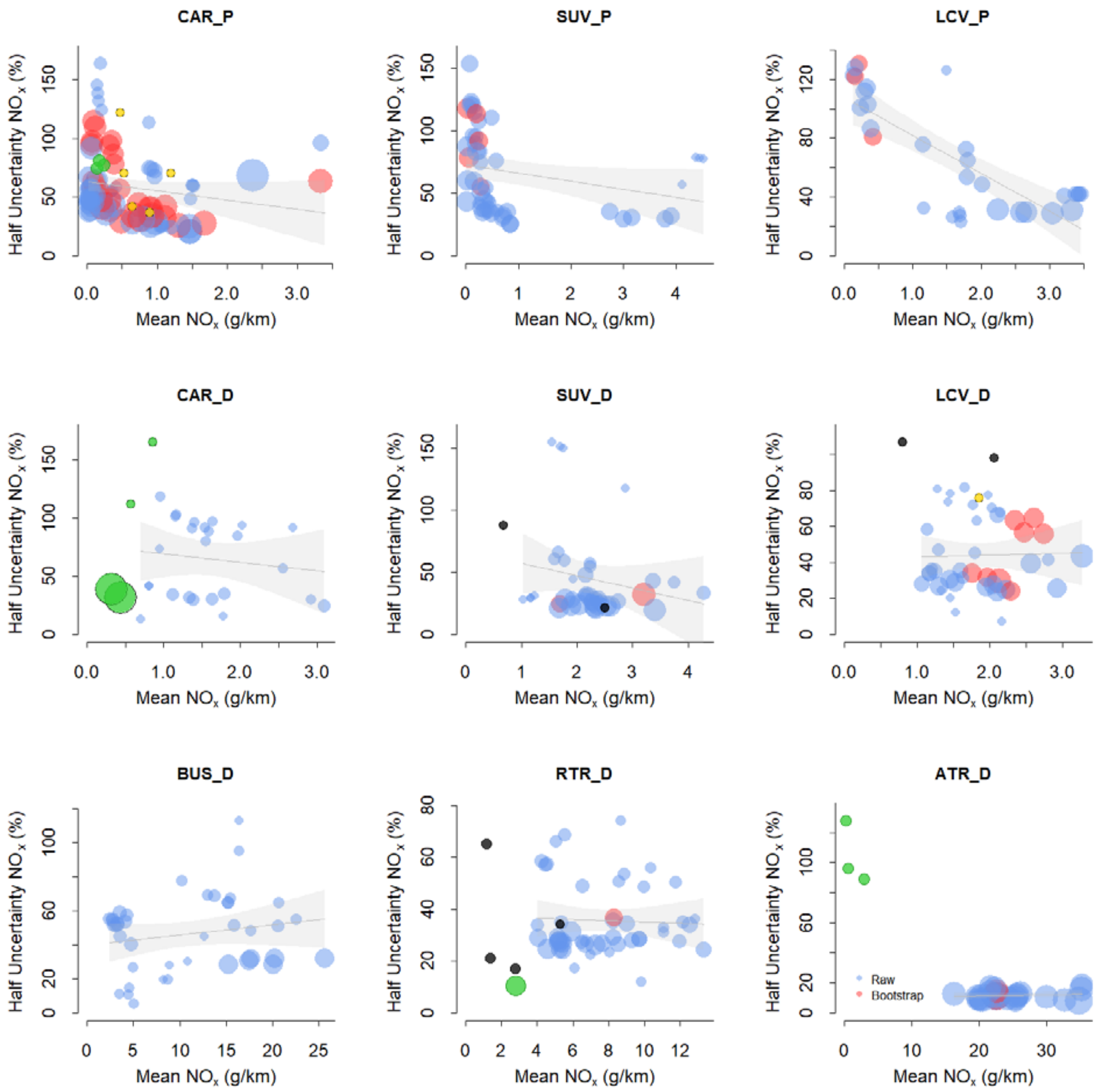


Figure 7.11 suggests that the results from the Australian laboratory testing programmes with real-world drive cycles, as well as from on-road PEMS studies across the world, provide a generally consistent picture in terms of uncertainty. An important factor is sample size. PEMS studies with large sample sizes (Gierczak et al., 2007; O'Driscoll et al., 2016) have relatively low levels of uncertainty, as expected. Large bubbles (large sample size) can be seen to tend to 'sink to the bottom' of the charts (lower uncertainty), which is not surprising, but worth pointing out here in the light of future VEPM improvement programmes (sample size matters!).

An interesting result is seen for the PEMS data collected for articulated diesel trucks (Grigoratos et al., 2019). Euro VI trucks have relatively small emission factors but significantly higher levels of uncertainty. The

New Zealand PEMS data for diesel trucks and diesel SUVs are consistent with overseas studies. The diesel LCV data, however, appear to have relatively high uncertainty.

It is noted that the New Zealand PEMS testing included six petrol passenger vehicles but they belonged to different vehicle classes, apart from two vehicles (petrol SUV Euro 3, new). However, the small sample size (n = 2) excluded these data from further use. The results are included in Table 7.1 for the interested reader.

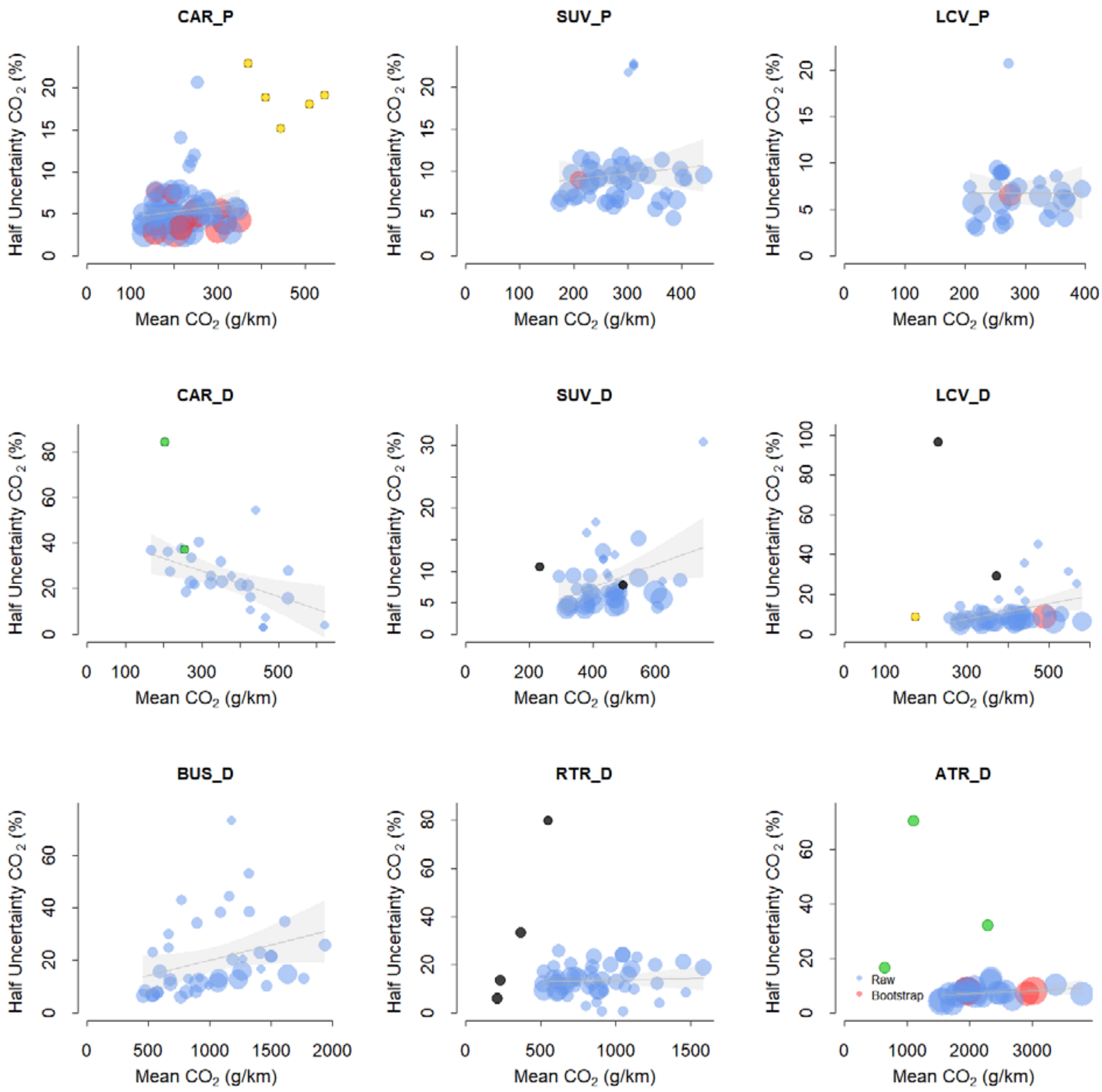
The on-road PEMS results for hot-running CO_2 emission factors are shown in Table 7.2. As before, high levels of uncertainty are associated with small sample size (n = 2). The emission factors are also shown in Figure 7.12, which combines the PEMS data with the analysis of the Australian emissions database (shown earlier in Figure 7.9).

Table 7.2 Analysis of published real-world (PEMS) hot-running CO_2 emission factors

Vehicle Class	Country	Traffic situation (Road Gradient)	Study Type	Mean EF (g/km)	Sample size	Uncertainty (%)	Reference
PC-P E_0	UK	urban (none)	2	369	3	23%	Daham 2009
PC-P E_1	UK	urban (none)	2	444	3	15%	Daham 2009
PC-P E_2	UK	urban (none)	2	511	3	18%	Daham 2009
PC-P E_3	UK	urban (none)	2	546	3	19%	Daham 2009
PC-P E_4	UK	urban (none)	2	409	3	19%	Daham 2009
LCV-D E_3	UK	urban-rural (unknown)	2	174	3	8%	Hadavi 2012
PC-D US_Tier 2	US	urban (variable)	3	255	3	37%	Thompson 2014
PC-D US_Tier 2	US	highway (variable)	3	144	2	16%	Thompson 2014
PC-D US_Tier 2	US	hilly (variable)	3	204	3	84%	Thompson 2014
HDV-D E_VI	EU	low speed (variable)	3	2284	5	32%	Grigoratos 2019
HDV-D E_VI	EU	medium speed (variable)	3	1103	5	71%	Grigoratos 2019
HDV-D E_VI	EU	high speed (variable)	3	645	5	17%	Grigoratos 2019
HDV-D E_1_used	NZ	low speed - urban (variable)	3	548	3	80%	NZ 2019
HDV-D E_1_used	NZ	medium speed - motorway (variable)	3	350	2	268%	NZ 2019
HDV-D E_1_used	NZ	medium speed - rural (variable)	3	258	2	88%	NZ 2019
HDV-D E_2_new	NZ	low speed - urban (variable)	3	366	4	33%	NZ 2019
HDV-D E_2_new	NZ	high speed - motorway (variable)	3	232	4	14%	NZ 2019
HDV-D E_2_new	NZ	medium speed - rural (variable)	3	210	4	6%	NZ 2019
HDV-D E_V_new	NZ	low speed - urban (variable)	3	435	2	10%	NZ 2019
HDV-D E_V_new	NZ	high speed - motorway (variable)	3	203	2	19%	NZ 2019
HDV-D E_V_new	NZ	medium speed - rural (variable)	3	180	2	36%	NZ 2019
SUV-D E_1_used	NZ	low speed - urban (variable)	3	317	2	22%	NZ 2019
SUV-D E_1_used	NZ	high speed - motorway (variable)	3	295	2	98%	NZ 2019
SUV-D E_1_used	NZ	medium speed - rural (variable)	3	192	2	152%	NZ 2019
SUV-D E_4_new	NZ	low speed - urban (variable)	3	497	3	8%	NZ 2019
SUV-D E_4_new	NZ	high speed - motorway (variable)	3	242	2	27%	NZ 2019
SUV-D E_4_new	NZ	medium speed - rural (variable)	3	233	3	11%	NZ 2019
SUV-P E_3_new	NZ	low speed - urban (variable)	3	382	2	257%	NZ 2019
SUV-P E_3_new	NZ	medium speed - rural (variable)	3	195	2	168%	NZ 2019
LCV-D E_4_new	NZ	low speed - urban (variable)	3	373	3	29%	NZ 2019
LCV-D E_4_new	NZ	medium speed - motorway (variable)	3	236	2	286%	NZ 2019
LCV-D E_4_new	NZ	medium speed - rural (variable)	3	228	3	96%	NZ 2019
LCV-D E_5_new	NZ	low speed - urban (variable)	3	387	2	101%	NZ 2019
LCV-D E_5_new	NZ	high speed - motorway (variable)	3	283	2	52%	NZ 2019
LCV-D E_5_new	NZ	medium speed - rural (variable)	3	220	2	18%	NZ 2019

Figure 7.12 suggests that the results for CO_2 are more stable than those for NO_x, with generally lower levels of uncertainty. However, there appears to be a clear distinction between 'well-behaved' laboratory data (real-world drive cycles) and on-road PEMS testing. PEMS testing generally exhibits significantly higher levels of uncertainty, which can also fluctuate widely. The exception is diesel SUVs, where the New Zealand PEMS data aligns well with the Australian laboratory data.

Figure 7.12 Uncertainty half range in the mean hot-running CO_2 emission factors for nine vehicle classes (dot size reflects sample size) – blue/red dots = Australian laboratory data (classical parametric/ bootstrap); black dots = New Zealand PEMS data (study type 3); yellow dots = PEMS data (within-vehicle variance only, study type 2); green dots = PEMS data (between-vehicle variance only, study type 3)



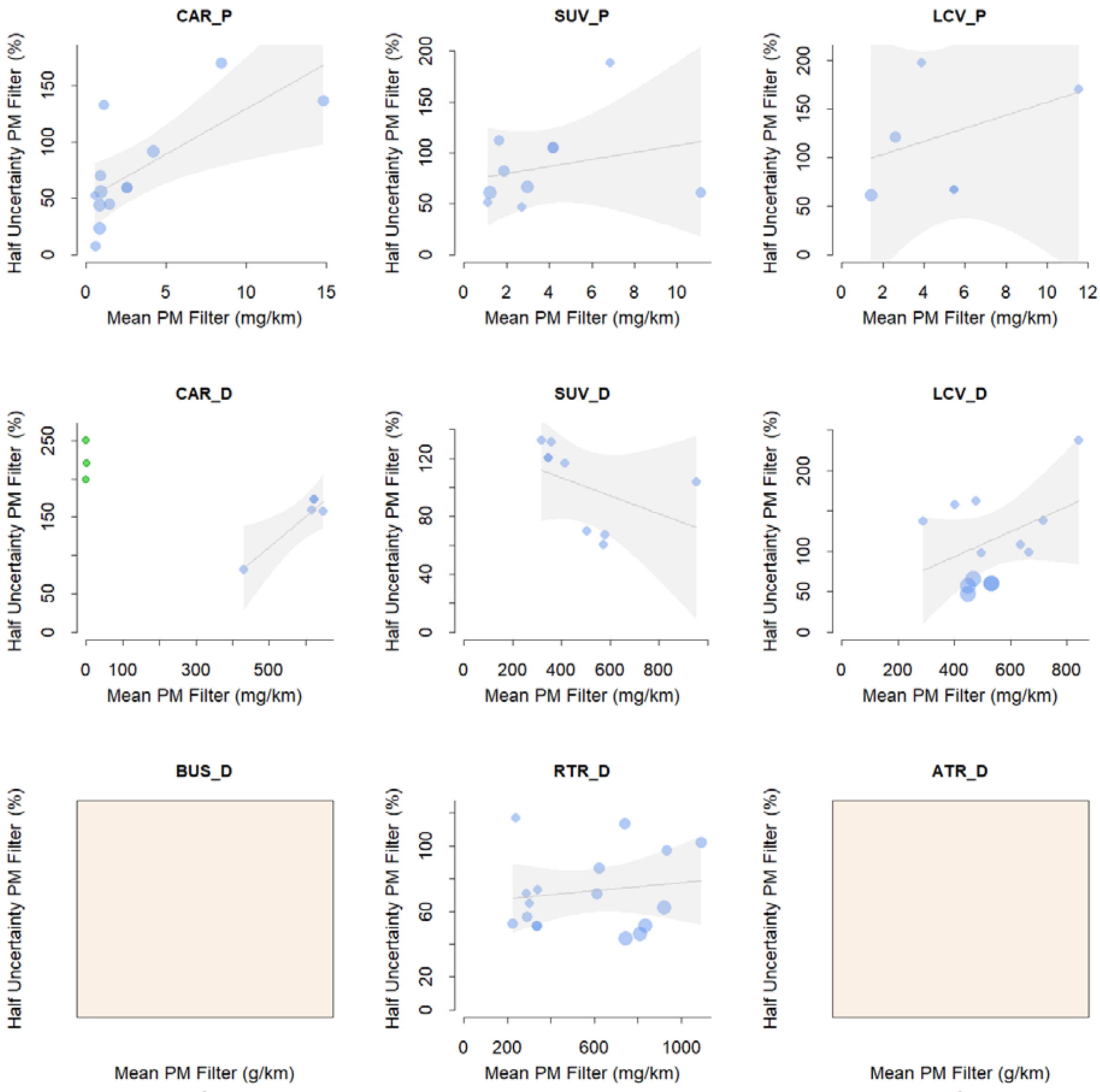
The on-road PEMS results for hot-running exhaust PM emission factors are shown in Table 7.3.

Table 7.3 Analysis of published real-world (PEMS) hot-running exhaust PM emission factors

Vehicle Class	Country	Traffic situation (Road Gradient)	Study Type	Mean EF (mg/km)	Sample size	Uncertainty (%)	Reference
PC-D US_Tier 2	US	urban (variable)	3	0.23	2	250%	Thompson 2014
PC-D US_Tier 2	US	highway (variable)	3	0.02	2	199%	Thompson 2014
PC-D US_Tier 2	US	hilly (variable)	3	1.19	2	220%	Thompson 2014
HDV-D E_1_used	NZ	low speed - urban (variable)	3	727.20	3	152%	NZ 2019
HDV-D E_1_used	NZ	medium speed - motorway (variable)	3	701.61	2	219%	NZ 2019
HDV-D E_1_used	NZ	medium speed - rural (variable)	3	142.69	2	97%	NZ 2019
HDV-D E_2_new	NZ	low speed - urban (variable)	3	353.75	4	42%	NZ 2019
HDV-D E_2_new	NZ	high speed - motorway (variable)	3	267.31	4	43%	NZ 2019
HDV-D E_2_new	NZ	medium speed - rural (variable)	3	176.86	4	73%	NZ 2019
HDV-D E_V_new	NZ	low speed - urban (variable)	3	45.79	2	177%	NZ 2019
HDV-D E_V_new	NZ	high speed - motorway (variable)	3	14.88	2	237%	NZ 2019
HDV-D E_V_new	NZ	medium speed - rural (variable)	3	18.33	2	160%	NZ 2019
SUV-D E_1_used	NZ	low speed - urban (variable)	3	210.03	2	198%	NZ 2019
SUV-D E_1_used	NZ	high speed - motorway (variable)	3	151.44	2	43%	NZ 2019
SUV-D E_1_used	NZ	medium speed - rural (variable)	3	101.41	2	55%	NZ 2019
SUV-D E_4_new	NZ	low speed - urban (variable)	3	78.59	3	35%	NZ 2019
SUV-D E_4_new	NZ	high speed - motorway (variable)	3	38.23	2	170%	NZ 2019
SUV-D E_4_new	NZ	medium speed - rural (variable)	3	27.08	3	93%	NZ 2019
SUV-P E_3_new	NZ	low speed - urban (variable)	3	2.16	2	122%	NZ 2019
SUV-P E_3_new	NZ	medium speed - rural (variable)	3	1.79	2	496%	NZ 2019
LCV-D E_4_new	NZ	low speed - urban (variable)	3	62.99	3	103%	NZ 2019
LCV-D E_4_new	NZ	medium speed - motorway (variable)	3	29.43	2	331%	NZ 2019
LCV-D E_4_new	NZ	medium speed - rural (variable)	3	44.64	3	101%	NZ 2019
LCV-D E_5_new	NZ	low speed - urban (variable)	3	4.13	2	118%	NZ 2019
LCV-D E_5_new	NZ	high speed - motorway (variable)	3	2.64	2	133%	NZ 2019
LCV-D E_5_new	NZ	medium speed - rural (variable)	3	2.99	2	199%	NZ 2019

The overseas on-road PEMS data were quite limited, with data available for only a small vehicle sample (n = 2) for one vehicle class (CAR_D). The uncertainty ranges are very high, but this is mainly due to the small sample size in combination with a small emission factor. In the absence of useful overseas data, the New Zealand PEMS data are a welcome addition. The emission factors are shown in Figure 7.13, which combines the PEMS data with the analysis of the Australian emissions database. The results are relatively consistent, although uncertainty is generally high.

Figure 7.13 Uncertainty half range in the mean hot-running PM emission factors for nine vehicle classes (dot size reflects sample size) – blue/red dots = Australian laboratory data (classical parametric/ bootstrap); black dots = New Zealand PEMS data (study type 3); yellow dots = PEMS data (within-vehicle variance only, study type 2); green dots = PEMS data (between-vehicle variance only, study type 3)



7.6 Comparison of PEMS and VEPM emission factors

To provide an initial and very high-level indicator of the performance of VEPMs outputs, a comparison of the published literature and New Zealand PEMS was undertaken against equivalent VEPM emission factors. Tables containing a detailed comparison of the published testing and equivalent VEPM-calculated emission factors are provided in Appendix C. This high-level comparison showed that on average, the:

- PEMS tailpipe PM emission factors were a factor of 2.7 times higher than VEPM emission factors
- PEMS NO_x emission factors were a factor of 1.6 times higher than VEPM emission factors
- PEMS CO_2 emission factors were a factor of 1.7 times higher than VEPM emission factors.

In summary, this comparison suggested there was a significant difference among the PEMS data that were considered in this study and that the VEPM was likely under-predicting real-world emissions. This finding supported the need to collect real-world emission and fuel use data in New Zealand, with the aim of improving the performance of the VEPM.

7.7 Quantifying uncertainty in emission factors

The final step was to derive estimates of plausible ranges in emission factors using the data analysis presented in the previous sections. The uncertainty information presented in Figure 7.11, Figure 7.12 and Figure 7.13 was used for this purpose.

The selected approach was to fit a curve to the data and determine the mathematical relationships between the response variable (% half uncertainty) and the predictor variable (hot-running emission factor). This provided the link with VEPM, where after identifying the corresponding vehicle class, the (mean) VEPM emission factors were used as input to predict the plausible range in uncertainty.

Figure 7.11, Figure 7.12 and Figure 7.13 show that the available uncertainty information based on the analysis of Australian laboratory testing data is reasonably well spread out over the range of emission factors. However, this is not the case for the available PEMS data, which are scarce and clustered in narrow emission factor ranges. In addition, the laboratory test data did not include recent technology vehicles, which are clearly a point of attention for specific vehicle classes (eg HDVs).

To address these issues, the data were further combined before the curves were fitted. A more aggregated vehicle classification was used (see Figure 7.14); that is:

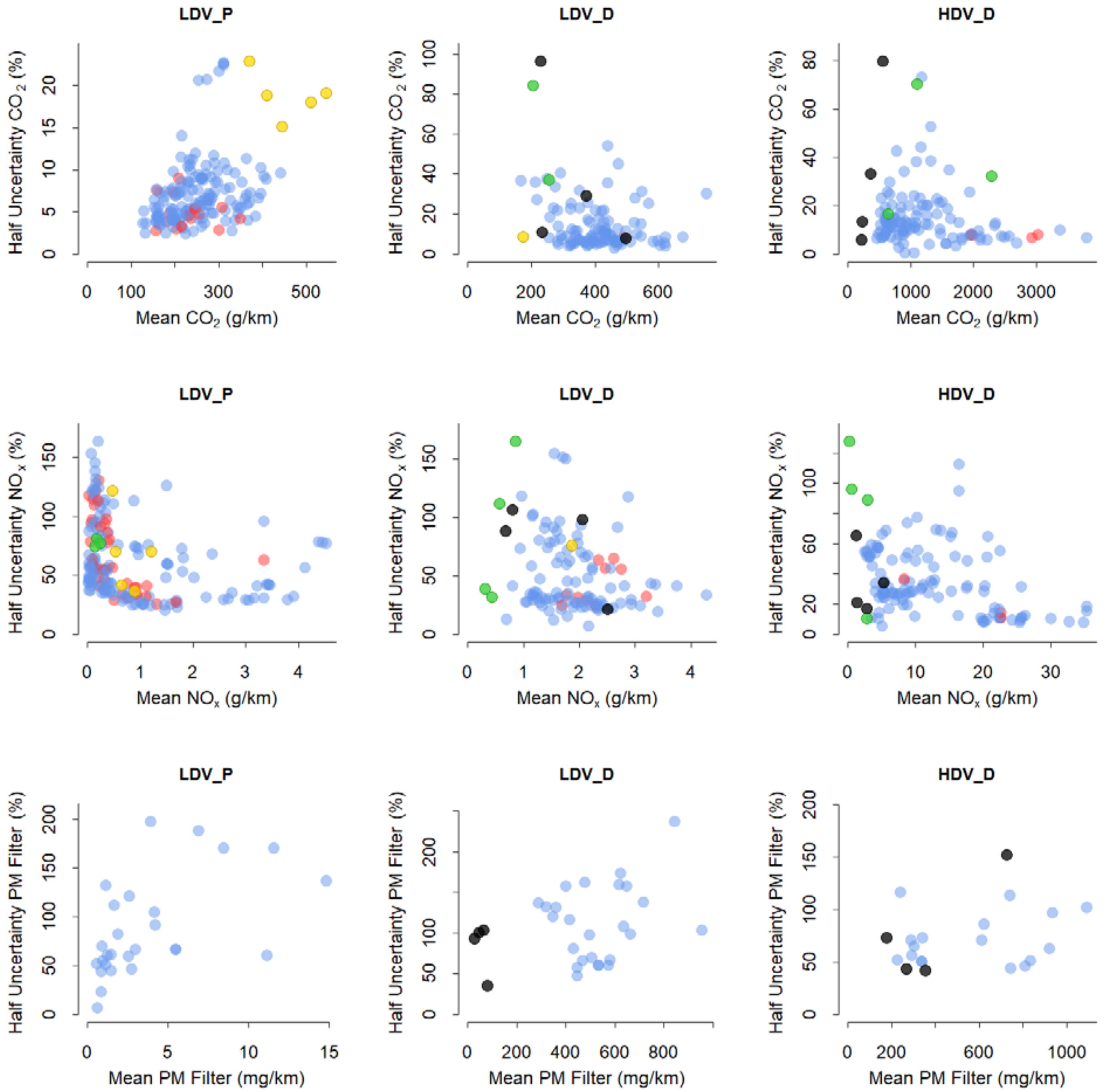
1. petrol LDVs (car, SUV, LCV)
2. diesel LDVs (car, SUV, LCV)
3. diesel HDVs (rigid truck, articulated truck, bus).

It was expected that this more aggregated data would provide results that were more robust. However, it became clear that a single curve was not going to describe the uncertainty in emission factors very well. In fact, the 'uncertainty in the uncertainty estimates' was large, as is evident by the wide vertical spread in Figure 7.14.

The approach therefore was to estimate a 'typical' value that depended on the absolute emission factor value and (aggregated) vehicle class, as well as a plausible range (minimum and maximum) for uncertainty in the emission factor. The plausible range could then be used in a sensitivity analysis in the UET, as discussed in Chapter 9.

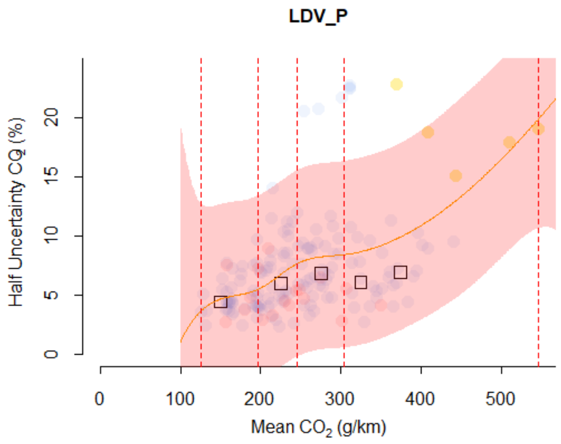
There are several ways to fit a curve to data; examples are (linear) interpolation, linear regression, polynomial regression, non-linear regression, piecewise linear regression, local regression and splines. There are also other statistical methods available to achieve linearity and simplify models, such as data transformations.

Figure 7.14 Uncertainty half range in the mean hot-running emission factors for three aggregated vehicle classes, blue/red dots = Australian laboratory data (classical parametric/bootstrap), black dots = New Zealand PEMS data (study type 3), yellow dots = PEMS data (within-vehicle variance only, study type 2), green dots = PEMS data (between-vehicle variance only, study type 3)



Regression splines are a particularly flexible approach for curve fitting and are often used in practice. Splines create smooth curves that can take almost any shape. Splines divide the predictor variable range into distinct regions and fit polynomial functions within these regions. The polynomials are constrained so that they join smoothly at the region boundaries (called 'knots'). An example of such a fit is shown in Figure 7.15 for CO_2- and petrol-fuelled LDVs.

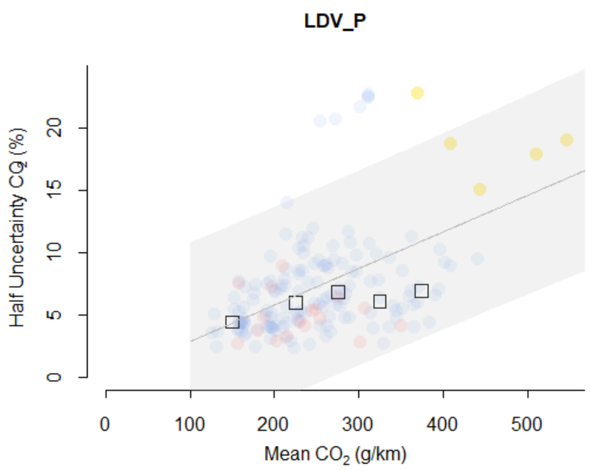
Figure 7.15 Fitting regression splines (df = 6) to petrol LDV CO_2 uncertainty data. The squares show median values calculated for bins with a minimum sample size of 10. The red solid line shows the mean prediction and the shaded red polygon shows the 95% prediction interval. Vertical red dashed lines show the knot locations



The fitted splines appear to describe the data well, and a cross-validation approach can be used to test different spline fits and produce the best possible fit without overfitting the data. The issue, however, is that the fitted splines suggest an increase in uncertainty. This relationship is counterintuitive and it is a good example of what happens when one deals with incomplete information. This result is largely caused by the PEMS data. As expected, the PEMS data exhibit a higher level of uncertainty than laboratory tests and are concentrated at the right side of the plot. The fitted splines model effectively reflects the limitation in available data, rather than a real trend with a physical explanation. In the future, using more PEMS data could help to resolve the issue and provide a plausible fit. However, for the purposes of this study and using the currently available data, a method that was more robust to the limitations of the uncertainty data was required.

Figure 7.16 shows the results for a linear regression fit. Although the fitted line is less flexible and more robust to 'outliers', it still suggests an implausible increase in uncertainty.

Figure 7.16 Fitting a linear regression function to petrol LDV CO_2 uncertainty data. The squares show the median values calculated for bins with a minimum sample size of 10. The grey solid line shows the mean prediction and the shaded grey polygon shows the 95% prediction interval



As a more robust solution, the following three values were calculated: 2.5%, 50% (median) and 97.5%. The results are shown in Figure 7.17. The benefit of this simple approach was that it still reflected the limited PEMS data, which were expected to provide a better estimate of real-world uncertainty in emission factors.

Figure 7.17 Estimating 2.5%, 50% and 97.5% values for petrol LDV CO_2 uncertainty data. The squares show the median values calculated for bins with a minimum sample size of 10

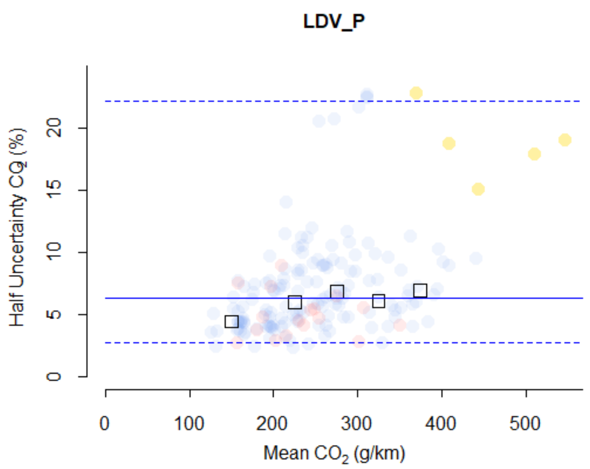


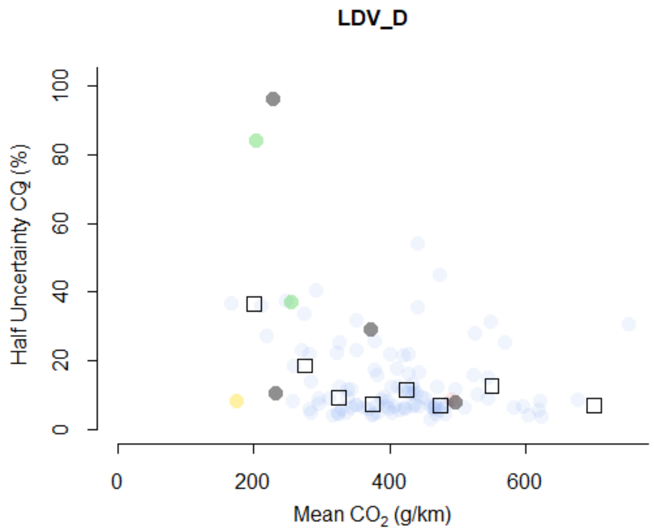
Table 7.4 summarises the percentile values for all three vehicle classes and three pollutants.

Table 7.4 Percentile values by vehicle class and pollutant

Vehicle class	Substance	2.5%	50.0%	97.5%
LDV_P	CO2	3%	6%	22%
LDV_D	CO2	4%	9%	84%
HDV_D	CO2	3%	13%	71%
LDV_P	NOx	25%	56%	131%
LDV_D	NOx	15%	39%	152%
HDV_D	NOx	8%	29%	96%
LDV_P	PM	17%	67%	192%
LDV_D	PM	35%	102%	187%
HDV_D	PM	42%	68%	152%

However, in some cases this approach may be too simplified. For instance, in Figure 7.14 there appears to be a trend of increasing uncertainty with decreasing emission factor values in some plots. Figure 7.18 shows an example where the computed median values (black squares) for binned uncertainty data are increasing for lower CO_2 emission factors. Intuitively this makes sense – lower emission factors are achieved with progressively more advanced engine and emission control technology, which can also be more sensitive (in a relative sense) to variability in driving behaviour, ambient conditions and so on.

Figure 7.18 Diesel LDV CO_2 uncertainty data. The squares show the median values calculated for bins with a minimum sample size of 10

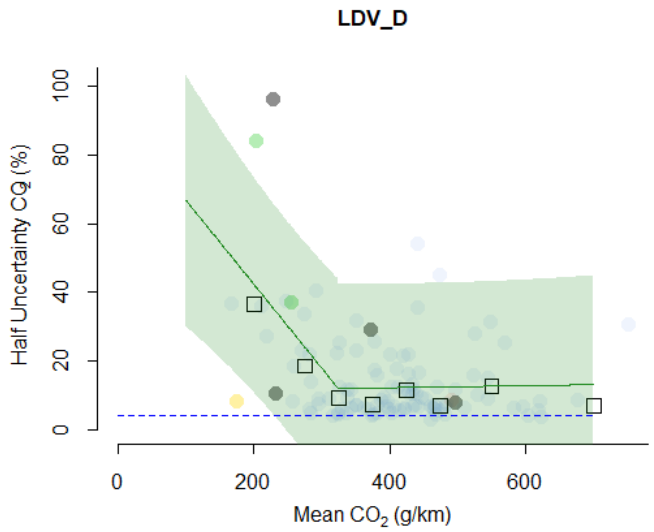


If the percentile approach is used, uncertainty will likely be underestimated for lower emission factors and overestimated for higher emission factors. Piecewise linear regression is used to achieve further refinement in curve fitting. This type of regression is capable of approximating overall systems behaviour with simple functions while preserving the desired level of flexibility and accuracy. The data are described by two or more straight lines that are connected at breakpoints and the fitted model predicts the most plausible values, as well as the 95% prediction intervals.

As a first step, the Davies test was used for each vehicle class and substance to determine whether a breakpoint was required. If it was not ($p \geq 0.05$), then the simple percentile approach was used. If it was ($p < 0.05$), segmented regression was used to determine the breakpoint and estimate the model coefficients for the piecewise linear model.[2] The results are illustrated in Figure 7.19, which shows implausible negative uncertainty values predicted (lower 95% confidence limit) for a certain range of emission factors. To remedy this, the minimum uncertainty was set as the 2.5% value (see Table 7.4), which is also shown in Figure 7.19 (the blue dashed line).

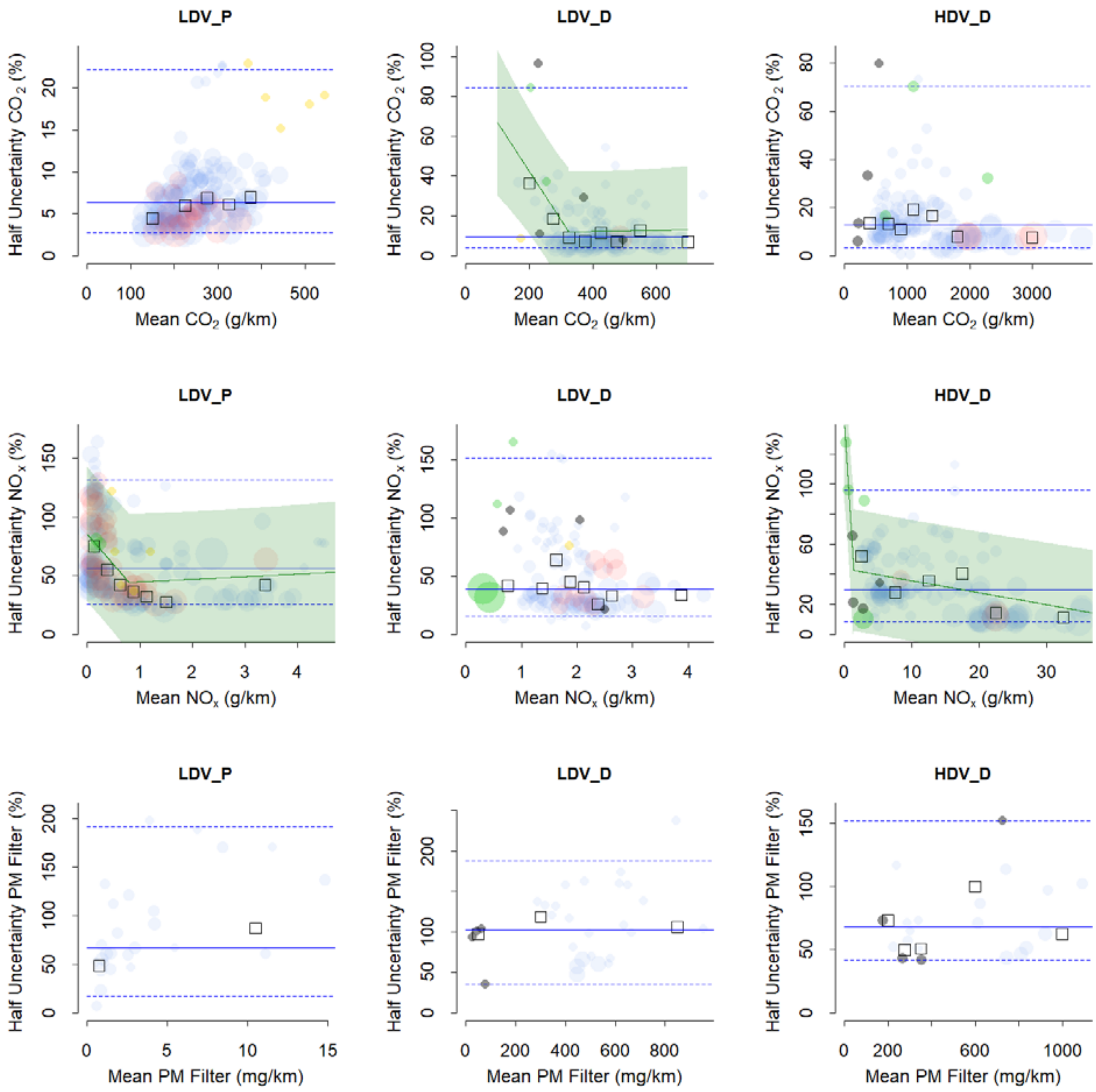
[2] It is noted that the Davies test was also applied for multiple breakpoints. However, this did not always work very well. For instance, in Figure 7.19, the resulting multi-line models show implausible behaviour and a sharp drop in uncertainty at low emission factor values. Expert judgement and visual examination were therefore used to arrive at a plausible end result.

Figure 7.19 Fitting a piecewise linear regression function to diesel LDV CO_2 uncertainty data. The squares show the median values calculated for bins with a minimum sample size of 10. The green solid line shows the mean prediction and the shaded green polygon shows the 95% prediction interval. The blue dashed line shows the 2.5% value



The final results are illustrated in Figure 7.20. The simple percentile approach was most often applied, showing that no statistically significant breakpoints ($p < 0.05$) could be identified in the data. This can be seen in the large scatter and uncertainty in the estimated uncertainty in the emission factors in the figure. For three cases, a more refined curve could be fitted (piecewise linear regression), although the plausible range in uncertainty remains high.

Figure 7.20 Fitting mathematical models to predict uncertainty half range in the mean hot-running emission factors for three aggregated vehicle classes and three substances. The blue horizontal lines represent the 2.5%, 50% and 97.5% values. The green solid line shows the mean prediction and the shaded green polygon shows the 95% prediction interval for the piecewise linear regression models. The squares show the median values calculated for bins with a minimum sample size of 10



To account for the high level of uncertainty in the predicted emission factor uncertainty, the following approach was used:

1. Finalise the UET using the typical or 'most plausible' uncertainty values for each VEPM emission factor.
2. Conduct a sensitivity analysis where the impact of the 'uncertainty in the uncertainty estimates' is evaluated. This is done by varying the estimated uncertainty for a particular vehicle class and substance with the minimum and maximum value (OAT) and quantify the impact (sensitivity) on the study outcomes.

The fitted mathematical models shown in Figure 7.20 were used to estimate the typical value (median or piecewise linear model prediction) and the minimum and maximum plausible values. Table 7.4 (shown earlier) shows the input for the percentile approach. The piecewise linear regression models were used to create lookup tables for a wide range of emission factor input values at a high resolution (1 g/km for CO_2, 1 mg/km for NO_x and PM). The lookup tables were further constrained in the following two ways:

1. The minimum uncertainty value was set to the 2.5% values listed in Table 7.4.
2. Uncertainty values were not allowed to increase with increasing emission factors and were set to the last available emission factor before an increase.

As a final comment, quantification of uncertainty can be improved by adding more (PEMS) data to the analysis, once these become available. The fitted functions can then potentially be expanded to include more variables (eg average speed) and to use a more refined vehicle classification.

8 VEPM modifiers

The objectives of this chapter are to:

- identify the modifiers the VEPM uses to adjust emission factors
- estimate the uncertainty in VEPM modifiers that will be used in Chapter 9 to identify emission and fuel use knowledge gaps.

The six key VEPM emission factor modifiers in this study were:

- fuel correction factor, which changes over time and reflects the fuel specification for the year in which the VEPM is being run
- degradation in emissions over time as the VKT of the vehicles increases
- road gradient, which ranges between −6% and +6% – gradient correction factors are available in the VEPM for NO_x for petrol LDVs and NO_x and PM for diesel LDVs
- cold-start emissions, because emissions are substantially higher when a vehicle is started cold until the engine and catalyst warm up – the average trip length (used to calculate cold-start emissions) was set to 9.1 km (the national average trip length) and the ambient temperature (also used to calculate cold-start emissions) was set to 13ºC (approximately the middle of the range available in the VEPM)
- NO_x/NO_2 emissions, with NO_2 emissions calculated by applying a modifier to the NO_x emission factors
- brake and tyre wear, considering non-exhaust PM_{10} emissions for different vehicle classes from brake and tyre wear based on general weight brackets and number of axles.

These key modifiers relate largely to the NO_x/NO_2 and $PM_{2.5}$ from exhaust pollutants. In addition to these key modifiers, the following variables, which are much more set (or have been considered to have a lesser impact on the overall emission uncertainty contributions) were also included, with estimated uncertainties:

- calorific value
- fuel density
- CO_2 emission factor.

These added modifiers have an impact on the emission factors for the CO_2 and PM_{10} pollutants.

To allow the total uncertainty for each vehicle class to be calculated for the various pollutants, an uncertainty was assigned to each of the modifiers. The approach to assigning uncertainties, along with the average value and the plausible ranges for each of the modifiers, is described next.

8.1 Fuel correction factor

The fuel correction factor is included in VEPM as a modifier to account for the impact of fuel quality on vehicle emissions.

Fuel correction factors are calculated within the VEPM from pollutant-specific polynomial equations using fuel property data. The equations themselves have been assumed to be correct and may be a source of bias within the VEPM – however, this evaluation was outside the scope of this investigation.

For 2018, the VEPM calculates fuel correction indexes for each pollutant of interest based on the Euro 4 fuel specification. Each pollutant index is then divided by the pollutant index calculated using the VEPM's base fuel specification, to give the fuel correction factor for each pollutant.

To estimate the uncertainty associated with the fuel correction factor in 2018, fuel quality monitoring data for New Zealand (Trading Standards, 2020) was reviewed and relevant maximum and minimum fuel property values were tabulated.

Using the minimum and maximum fuel property data, minimum and maximum fuel correction factors for each pollutant of interest were determined, giving the following three estimates for the fuel correction factor for each pollutant:

- VEPM 2018 fuel correction factor
- minimum fuel correction factor calculated from fuel quality monitoring data
- maximum fuel correction factor calculated from fuel quality monitoring data.

In some cases, the VEPM-calculated fuel correction factor was outside the range calculated using the fuel quality monitoring data. To estimate the fuel correction factor half uncertainty for each pollutant, the known bounds method was used. The fuel correction factor half uncertainty was found to range between 4% and 20%.

The uncertainties calculated using the known bounds method were considered most appropriate for this project, even though this method deviates from the classic parametric approach. This is because the maximum and minimum fuel correction factors derived from the New Zealand trading standards are considered relatively set and the range would be highly unlikely to fall outside these values. The above approach to uncertainty acknowledges this. Using the classical parametric approach and entering the three values determined with sample size n = 3 does not account for the maximum and minimum values being the upper and lower values of the plausible range and therefore, the uncertainties estimated using the classical parametric method are much larger (by up to 38%). As we knew the uncertainty would not be this large, the classical parametric method was not adopted for use in determining the uncertainty.

The uncertainty calculated in this project could be further refined by obtaining data for the 79 individual fuel property tests undertaken, calculating the individual associated fuel correction factors for each pollutant, and estimating the uncertainty using the method described earlier in Section 7.7.

8.2 Degradation correction

The VEPM contains degradation factor estimates for pollutants of interest in several different vehicle classes, drawn from a range of sources. We noted the following discrepancies in the source of the degradation factors used in the VEPM:

- The VEPM 6.1 Update Technical Report cites the following sources:
  - European gasoline (European Environment Agency, 2019)
  - Japanese domestic imports, as described in Energy & Fuels Research Unit (2008)
  - light-duty diesel, European Auto-Oil study as described in Energy & Fuels Research Unit (2008) and Energy & Fuels Research Unit (2011)
  - heavy-duty diesel, Euro Auto-Oil study + US Environmental Protection Agency M6.HDE.001 as described in Energy & Fuels Research Unit (2008).

The degradation data from the tab 'EU & NZ Degradation' and 'Japan Front' for the vehicle classes of interest (petrol car, diesel car, petrol LCV, diesel LCV, rigid HDV, articulated HDV and bus) were analysed to estimate the uncertainty in the degradation factor for each pollutant of interest.

The classic parametric method described earlier in Section 7.3 was used to estimate the uncertainty in the degradation factor for each pollutant of interest. The number of data points for each vehicle class ranged from 14 to 112. All data sets had a coefficient of variation less than 0.3, indicating that a normal distribution was a reasonable assumption. A 95% confidence interval was assumed and plausible ranges for the mean degradation factor for each pollutant in each vehicle class of interest were calculated, using the appropriate t-statistic. From the calculated mean value plausible ranges, an estimate of the uncertainties was then calculated. The uncertainties in degradation were found to range between 6% and 28%.

8.3 Gradient correction

The VEPM uses a polynomial equation to calculate a gradient correction factor for several different vehicle emission classes. As noted previously for the fuel correction factor, the polynomial equation itself has been assumed to be correct and may be a source of bias within the VEPM. The polynomial has unique coefficients for each of the road gradients listed in Table 6.1 (−6% to 6%). The UET calculates the gradient correction factor for each road gradient for each pollutant and these are multiplied by the percent of total AADT in each grade to give a weighted average gradient correction factor for each vehicle type and emission standard (Euro 1, Euro 2, etc).

To estimate the potential uncertainty associated with the gradient correction factor, the mean, minimum and maximum gradient correction factors within each vehicle type (eg petrol cars) were calculated for each pollutant, using the individually calculated weighted average gradient correction factors in accordance with the nationwide gradient breakdown presented in Table 6.1 for each emission standard (ie ECE 15/00, Pre-Euro–Euro 4).

The gradient correction factor uncertainty for each pollutant (where relevant) within each vehicle class was estimated using the classical parametric approach described in Section 7.3, with sample sizes (n) varying between 5 and 6. Notably, this sample size is considered small (the larger the sample, the lower the uncertainty in the mean value and the narrower the confidence interval) – using a small sample size can reduce the accuracy of the uncertainty that is calculated. The uncertainties calculated were between 1% and 11%.

To rationalise this, the half uncertainty for each pollutant within each vehicle class was also estimated by the known bounds method. Using this approach, the half uncertainties in gradient correction factors were found to range between 1% and 22% – that is, some of the uncertainties were higher than those estimated by the classical parametric approach. While it could have been more conservative to adopt these larger uncertainties, the uncertainties estimated by the classical parametric approach were considered reasonable and therefore, they were adopted for use in the UET, for consistency.

8.4 Cold-start emissions correction

Cold-start emissions uncertainties are known to be notoriously hard to estimate, due to data limitations. In previous international uncertainty estimation studies, the uncertainty in cold-start emissions has been assumed to be the same as those for the corresponding hot-start emissions (Kouridis et al., 2010).

This study adopted the same assumption. It is recommended that this assumption be tested when new real-world emissions data become available.

8.5 NO_x/NO_2 emission correction

The VEPM contains NO_x/NO_2 emission correction estimates for several different vehicle classes. It draws its NO_x/NO_2 emission corrections from Chapter 1.A.3 of the *EMEP/EEA Air Pollutant Emission Inventory Guidebook* (the Guidebook) (European Environment Agency, 2019), The Guidebook contains a section on NO_x speciation that provides details of the mass fraction of NO_2 in NO_x (f-NO_2) by vehicle class and emission control technology. The Guidebook draws its f-NO_2 data from two studies undertaken in Europe – the AEA

Technology study by Grice et al. (2007) and informed by Smit (pers. comm., 2007). It presents the f-NO_2 data from both studies and provides a suggested value for each vehicle class and emission control technology.

For vehicle class (petrol car, diesel car, petrol LCV, diesel LCV, rigid HDV, articulated HDV and bus), the classic parametric method described earlier in Section 7.3 was used to estimate the uncertainty in the NO_x/NO_2 emission correction factor. The number of data points for each vehicle class ranged from 14 to 167. All data sets had a coefficient of variation less than 0.3, indicating that a normal distribution was a reasonable assumption.

Carslaw et al. (2011) reported on the issue of f-NO_2, using remote sensing device (RSD) data collected by Grice et al. (2009) and Jerksjö et al. (2008). To ensure the uncertainty estimated for f-NO_2 for this project using the Grice et al. (2007) and Smit (2007) study data was robust, f-NO_2 uncertainty was also estimated using the data from Grice et al. (2009) and Jerksjö et al. (2008). The range of f-NO_2 values from the Grice et al. (2009) and Jerksjö et al. (2008) data aligned with the Grice et al. (2007) and Smit (2007) estimates for each vehicle class. The f-NO_2 uncertainties estimated from the classic parametric approach, using all available data from the studies discussed above, were adopted for this study.

As for the degradation factor, a 95% confidence interval was assumed and plausible ranges for the mean NO_x/NO_2 correction factor for each pollutant in each vehicle class of interest was calculated using the appropriate t-statistic.

From the calculated mean value plausible ranges, an estimate of the uncertainties was then calculated. The uncertainties in NO_x/NO_2 correction factors were found to range between 3% and 18%.

8.6 Brake and tyre wear

The brake and tyre wear factor contributes to the portion of PM_{10} from non-exhaust emissions and is calculated by the VEPM to reflect the EMEP/EEA Guidebook method (European Environment Agency, 2019). The minimum and maximum variables from Tables 3-4 to 3-7 in this Guidebook were used to estimate the plausible range and average of factors for both internal combustion engine cars and LCVs.

The brake and tyre emission values for passenger cars, LCVs and HDVs that are calculated using the EMEP/EEA Guidebook method within the VEPM can be compared with other studies. TER (2020b) created a database of internationally published emission factors and compared the non-exhaust PM_{10} and $PM_{2.5}$ emissions from battery electric vehicles and internal combustion engine vehicles. A bootstrap simulation was conducted to estimate the grand mean and associated non-symmetric 95% confidence intervals for each non-exhaust PM aspect (tyres, brakes, road surface, road dust re-suspension), followed by a probabilistic analysis. This study estimated a PM_{10} mean non-exhaust emission factor (excluding re-suspended road dust) of 19.6 mg/km for internal combustion engine vehicles with a plausible range of 9.4 to 35.9 mg/km; that is, an asymmetric uncertainty of −52% to +83%. This broad range roughly aligned with the EMEP/EEA Guidebook method plausible ranges for passenger cars (7–20 mg/km) and LCVs (9–28 mg/km).

Further refinement could include obtaining the original data points used to inform each of the plausible ranges in the studies and applying the classic parametric approach to those data sets.

The half uncertainties for passenger car and LDV classes based on the EMEP/EEA Guidebook method ranges using the known bounds method were found to range from 52% to 57%.

A review of the literature provided evidence that brake and tyre wear particulate emissions may also occur in the $PM_{2.5}$ size range, not just PM_{10}. A recommendation is made in Section 12.1 to consider this issue in any update to emission models or related inventories, given the increasing importance of $PM_{2.5}$.

8.7 Other modifiers

The uncertainties for the following VEPM modifiers were also included in the UETs. The uncertainties for each of these modifiers were calculated as follows:

- Calorific value is a relatively well-known and set variable for each fuel type. Uncertainty for petrol and diesel was calculated using the classic parametric method described earlier in Section 7.3 with data sourced from the Ministry of Business, Innovation & Employment (2020) oil statistics for New Zealand. There were 47 data points for each fuel type. Uncertainties were found to range from 0.05% to 0.10%.
- Fuel density is a relatively well-known and set variable for each fuel type. Uncertainty was calculated using data from the VEPM and web-based fuel data sources (Engineering Toolbox, 2013), applying the known bounds method because of the limited data points available and the fact that this method better considers the known upper and lower bounds. Using the known bounds method, half uncertainties were found to range from 9% to 16%. The classic parametric method described in Section 7.3 determined values between 3% and 11%; therefore, the differences between the two methods were small.
- As the CO_2 emission factor is a function of the mass of CO_2 per volume of fuel used divided by the fuel calorific value and density, this is a relatively set variable. Uncertainty was estimated through applying the error propagation rules outlined in Section 5.5 for calorific value and density uncertainties, with incorporation of the data for CO_2 production per litre of fuel used from the Ministry for the Environment (2019). Final half uncertainty was estimated by applying the known bounds method because of the limited data points available. Half uncertainties were found to range between 1% and 5%.

8.8 Quantifying the sensitivity of modifiers

It was important to quantify whether the UET results were sensitive to varying uncertainties in the VEPM modifiers. Uncertainties in the modifiers were not expected to affect the overall results greatly, due to the modifier being a slight adjustment factor to the overall emission factor, which was the key input. In addition, it was noted that the uncertainties determined for the modifiers were an order of magnitude of 10 smaller than those determined for emission factors and therefore, they were not expected to have a large impact on the overall uncertainty contribution. To ensure this was the case, an OAT analysis was run for the fuel correction factor, gradient correction factor and NO_x/NO_2 correction factor, showing that the results of the UET were not sensitive to varying uncertainty in modifiers for the scenarios where:

- the uncertainty for each VEPM modifier was 50% of that calculated
- the uncertainty for each VEPM modifier was 150% of that calculated.

The same exercise was also undertaken for VKT, to determine whether uncertainty variation was likely to affect the results found from the UET. Using the same increase and decrease scenarios, this exercise also demonstrated that VKT was unlikely to have an impact on the results because of its relatively low uncertainty.

This demonstrated that while the uncertainty estimates for the VEPM modifiers could be further refined by incorporating information from the literature, they had a relatively low impact on the outcome of the UET results. Therefore, for this project, emphasis was put on the emission factors being the main contributor to the RI and uncertainty of the UET results.

8.9 Vehicle classes within the VEPM

The VEPM provides emission factors for each class of vehicle included in the model. The primary vehicle classes used in VEPM are:

- passenger cars – petrol

- passenger cars – diesel
- passenger cars – hybrid and electric
- LCVs – petrol
- LCVs – diesel
- heavy-duty trucks – rigid
- heavy-duty trucks – articulated
- buses.

The VEPM breaks each primary vehicle class into secondary subclasses, according to their use of emission control technology based on the relevant European standards. The VEPM also provides a tertiary subclass based on vehicle size or weight. The size subclasses for passenger vehicles are 'small', 'medium' and 'large-SUV-executive'. There are seven weight classes for HDVs, ranging from < 7.5 tonnes to > 32 tonnes. There are three weight classes for buses, ranging from < 15 tonnes (urban buses) to > 18 tonnes (intercity coaches).

The quantification of uncertainty in emission factors that is presented in Chapter 9 considers emission factors for all the VEPM's primary, secondary and tertiary vehicle subclasses.

9 Identifying emission and fuel use knowledge gaps

In this study, the VEPM was used to examine uncertainty in the predictions of traffic emissions, and a sensitivity analysis was used to apportion prediction variability to specific inputs and vehicle classes. The sensitivity analysis was undertaken using the UET described in Chapter 5, the modifiers described in this section and the uncertainty in emission factors detailed in Chapter 7. The results of the sensitivity analysis are presented in Chapter 9.

The key objectives of this chapter are to:

- provide an introduction to, and context for, the results
- identify the key knowledge gaps regarding vehicle emissions and fuel use
- target vehicles types for future vehicle emission measurement programmes that have relatively large:
  - impact (significant contribution to total emissions)
  - uncertainty in estimated emissions.

This chapter presents the results from running the UET (see Chapters 4 and 5) using the VEPM modifier uncertainties (see Section 8) and emission factor uncertainties (see Section 7). The results for each of the key pollutants are presented in two parts: the first part identifies the vehicle classes that have relatively high impact and uncertainty within the fleet and the second part breaks down the priority vehicle classes by emission reduction technology. The vehicle classes considered in the UET analysis are listed in Table 9.1.

Table 9.1 Vehicle classes considered in the UET

Vehicle category	Vehicle class					
Car	Petrol	Diesel	Hybrid	Plug-in hybrid	Electric	
LCV	Petrol	Diesel	Hybrid	Plug-in hybrid	Electric	
HDV: Diesel Rigid	3.5–7.5 t	7.5–10 t	10–20 t	20–25 t	25–30 t	> 30 t
HDV: Diesel Articulated	14–20 t	20–28 t	28–34 t	34–40 t	40–50 t	> 50 t
HDV: Electric	< 10 t	> 10 t				
Bus: Diesel Urban	< = 12 t	12–18 t				
Bus: Diesel Coach	12–18 t					
Bus: Electric	> 3.5 t					

Electric vehicles were excluded from the UET analysis as they do not have a tailpipe emission factor for the key pollutants.

In the part one results for each pollutant, each vehicle class was given a rank, which was determined by considering both the vehicle class contribution to total fleet emissions and the uncertainty contained within it. Therefore, a high-ranking vehicle had a relatively large contribution to the total fleet emissions as well as a relatively high uncertainty level. The sensitivity of the ranking to changes in uncertainty in the emission factor was then tested via an OAT analysis, which ran scenarios with varied uncertainty in the emission factor for each vehicle class, from the initial 50% down to 2.5% and up to 97.5%. The rankings of the vehicles under each of these uncertainty scenarios was compared. If the rankings did not show large changes, then we could be confident that the ranking presented for each pollutant was robust. An example of the UET and OAT analysis for NO_x is presented in Appendix A.

Part two of the results, considering the priority vehicle classes by emission reduction technology, facilitated the design of a focused and informative programme for emission and fuel use monitoring. The New Zealand vehicle fleet contains a mix of vehicles that have mostly been made to meet Japanese and European emission standards, with a small number of older vehicles that were built to meet the United Nations vehicle emission regulation ECE 15/04. The VEPM provides an equivalent European emission standard for vehicles built to Japanese standards. Both Japanese and European vehicles were included in the UET analysis. However, to reduce the complexity of the results, they have been presented as European equivalent standards. The emission reduction technology classes considered in the UET analysis are listed in Table 9.2.

Table 9.2 Emission reduction technology classes

Vehicle category	Emission technology class						
Car	Conventional	Euro 1	Euro 2	Euro 3	Euro 4	Euro 5	Euro 6
LCV	Conventional	Euro 1	Euro 2	Euro 3	Euro 4	Euro 5	Euro 6
HDV: Diesel Rigid	Conventional	Euro I	Euro II	Euro III	Euro IV	Euro V	Euro VI
HDV: Diesel Articulated	Conventional	Euro I	Euro II	Euro III	Euro IV	Euro V	Euro VI
HDV: Electric	Conventional	Euro I	Euro II	Euro III	Euro IV	Euro V	Euro VI
Bus: Diesel Urban	Conventional	Euro I	Euro II	Euro III	Euro IV	Euro V	Euro VI
Bus: Diesel Coach	Conventional	Euro I	Euro II	Euro III	Euro IV	Euro V	Euro VI

The VEPM breaks down the car and LCV emission class technologies further into small, medium and large vehicles. This is a useful way of refining the target vehicles to be potentially monitored.

A simplified worked example of the UET analysis for NO_x is shown in Figure 9.1. A detailed set of results for NO_x emission technology is presented in Appendix B. The UET computes the fleet-weighted emission factors in a format that emulates VEPM referencing and VEPM model inputs for the nationwide base case scenario, and then it subsequently determines the:

- RI of the vehicle class emissions (or emission technology emissions) to total fleet emissions
- confidence interval of the RI (lower and upper confidence limits determined by the plausible ranges)
- range of the RI confidence interval (the upper confidence limit minus the lower confidence limit)
- uncertainty contribution, indicating the vehicle class with the highest impact and highest uncertainty.

The results tables for each pollutant present a priority ranking for vehicle class (or emission technology) as determined by the highest uncertainty contribution.

Figure 9.1 Example of NO_X UET used for vehicle classes

Colour Key:
Data Gap
Unapplicable

$$E_{NO_x,URB,v} = E_{hot,NOx,v} \times f_{NO_x,v} \times s(m)_{NO_x,v} \times g(x)_{NO_x,v}$$

Direct from VFEM (No population/mileage breakdown)

Base year	Speed
2018	77

Emission Inventory

i	j	v		eijv	M1ijv	M2ijv		Eijv	Emission	Inventory
Substance	Situation	Vehicle class	VKT (% fleet)	Ehot (g/km)	f	s(m)	...	fleet emission (g/km)	Absolute Annual VKT	Total Emissions (kg)
NOx	NAT	Cars Petrol	66.34%	0.15	1.08	1.42	...	0.274	31677181713	13067936
NOx	NAT	Cars Diesel	7.75%	0.51	1.00	1.41	...	0.061	3702473079	2913331
NOx	NAT	Cars Hybrid		0.02	1.08	1.00	...			
NOx	NAT	Cars Plugin Hybrid		0.02	1.08	1.00	...			
NOx	NAT	Cars Electric					...			
NOx	NAT	LCVs Petrol	3.20%	0.66	1.08	1.49	...	0.036	1528013885	1705628
NOx	NAT	LCVs Diesel	15.69%	0.89	1.00	1.45	...	0.207	7491746355	9873559
...	...	...	...	...	...	...	...	...	...	...
			100%			Eij		0.859	47748151475	41037799

Uncertainty			Uncertainty					
Substance	Situation	Vehicle class	VKT (% fleet)	Ehot (g/km)	f	s(m)	g(x)	...
NOx	NAT	Cars Petrol	3%	78%	20%	8%	14%	...
NOx	NAT	Cars Diesel	6%	39%	5%	6%	3%	...
NOx	NAT	Cars Hybrid		84%	20%		14%	...
NOx	NAT	Cars Plugin Hybrid		84%	20%		14%	...
NOx	NAT	Cars Electric						...
NOx	NAT	LCVs Petrol	5%	51%	20%	28%	14%	...
NOx	NAT	LCVs Diesel	5%	39%	5%	9%	3%	...
NOx	NAT	LCVs Hybrid		84%	20%		14%	...
...	...	...	...	...	...	...	...	...

			%	g	(g)^2	Plausible Range		Uncertainty Contribution
Substance	Situation	Vehicle class	U-Eijv	U-Eijv	U-Eijv^2	LCL Eijv (g)	UCL Eijv (g)	Eijv to Eij (%)
NOx	NAT	Cars Petrol	76%	0.21	0.04	0.067	0.481	82%
NOx	NAT	Cars Diesel	39%	0.02	0.00	0.037	0.085	1%
NOx	NAT	Cars Hybrid						
NOx	NAT	Cars Plugin Hybrid						
NOx	NAT	Cars Electric						
NOx	NAT	LCVs Petrol	61%	0.02	0.00	0.014	0.057	1%
NOx	NAT	LCVs Diesel	40%	0.08	0.01	0.124	0.289	13%
NOx	NAT	LCVs Hybrid						
...	...	...	...	...	...	...	...	...
								100%

uncertainty emission inventory

%	g
U-Eij	U-Eij
27%	0.228

Emission Inventory

i	j	v	Relative Importance				
Substance	Situation	Vehicle class	RI	LCL RI	UCL RI	RNG RI	UCL - LCL
NOx	NAT	Cars Petrol	32%	10%	45%	10.2% - 45.1%	35%
NOx	NAT	Cars Diesel	7%	4%	10%	4.4% - 9.6%	5%
NOx	NAT	Cars Hybrid	0%				
NOx	NAT	Cars Plugin Hybrid	0%				
NOx	NAT	Cars Electric	0%				
NOx	NAT	LCVs Petrol	4%	2%	7%	1.7% - 6.5%	5%
NOx	NAT	LCVs Diesel	24%	16%	31%	16% - 30.7%	15%
...	...	...	...	...	...	...	...
			100%				

9.1 NO_x

9.1.1 Vehicle class

Priority ranking by vehicle class for NO_x is shown in Table 9.3.

Table 9.3 Priority ranking by vehicle class for NO_x

Priority ranking	Vehicle class	RI (Eijv /Eij) (%)	RI confidence interval (lower limit–upper limit) (%)	Range confidence interval (%)	Uncertainty contribution to emission inventory (%)
1	Car Petrol	31.8	10.4–45	34.5	78.1
2	LCV Diesel	24.1	14.7–31.6	16.8	16.4
3	Car Diesel	7.1	4.2–9.9	5.7	1.3
4	HDV Diesel Articulated 34–40 t	4.7	2.4–7	4.6	0.8
5	LCV Petrol	4.2	1.6–6.5	4.9	0.9
6	HDV Diesel Articulated 40–50 t	3.6	1.8–5.3	3.5	0.4
7	HDV Diesel Articulated 28–34 t	3.3	1.7–4.9	3.2	0.4
8	HDV Diesel Rigid 3.5–7.5 t	3.0	1.5–4.5	3.0	0.3
9	Bus Diesel Urban 12–18 t	3.2	1.9–4.6	2.7	0.3
10	HDV Diesel Rigid > 30 t	2.9	1.4–4.3	2.8	0.3
11	HDV Diesel Articulated > 50 t	2.7	1.4–4	2.7	0.3
12	HDV Diesel Rigid 25–30 t	2.5	1.2–3.7	2.4	0.2
13	HDV Diesel Rigid 20–25 t	2.1	1.1–3.2	2.1	0.2
14	HDV Diesel Articulated 20–28 t	1.7	0.9–2.6	1.7	0.1
15	HDV Diesel Rigid 10–20 t	1.6	0.8–2.3	1.6	0.1

As identified in Table 9.3, the priority vehicles classes in relation to the emissions of NO_x are petrol cars, diesel LCVs and diesel cars. The top three vehicle classes account for approximately 95% of the total uncertainty in the NO_x UET (diesel cars 1%, diesel LCVs 16%, petrol cars 78%). The OAT NO_x analysis confirms that the rankings of all 15 vehicle classes are not sensitive to changes in emission factor uncertainty. The results of the OAT analysis demonstrate that the NO_x ranking of priority vehicles is robust.

9.1.2 Emission technology

Priority ranking by vehicle class and emission technology for NO_x is shown in Table 9.4.

Table 9.4 Priority ranking emission by technology class for NO_x

Priority ranking	Vehicle class	Emission technology	RI (Eijv /Eij) (%)	RI confidence interval (lower limit–upper limit) (%)	Range confidence interval (%)	Uncertainty contribution to emission inventory (%)
1	LCV_Diesel	Euro 4 N1-III diesel particulate filter (DPF)	9.2	5.2–12.8	7.6	28.3
2	LCV_Diesel	Euro 5 N1-III DPF	7.5	4.3–10.6	6.3	19.1
3	PC_Petrol	ECE 15/04 Medium 1.4–2.0 l	4.1	2.1–6	3.9	6.7
4	PC_Petrol	Euro 1 Medium J78, J88 1.4–2.0 l	3.1	1.1–5.1	4.1	7.2
5	PC_Petrol	Euro 1 Large-SUV-Executive > 2.0 l	2.5	0.9–4	3.1	4.1
6	LCV_Diesel	Euro 3 N1–III DPF	2.5	1.4–3.7	2.3	2.2
7	PC_Petrol	Euro 1 Medium 1.4–2.0 l	2.0	0.8–3.3	2.5	2.6
8	HDV_Diesel	Euro IV Articulated 50–60 t SCR > 50 t	2.2	1.1–3.3	2.2	2.0
9	PC_Petrol	ECE 15/04 Large-SUV-Executive > 2.0 l	2.2	1.1–3.3	2.2	2.0
10	LCV_Petrol	Conventional N1-III	2.0	0.9–3.2	2.3	2.3
11	PC_Petrol	New Zealand new Large > 2.0 l	2.1	1.1–3.1	2.1	1.8
12	HDV_Diesel	Conventional Articulated > 50 t	2.0	1–3	2.0	1.7
13	PC_Diesel	Euro 4 Large-SUV-Executive DPF > 2.0 l	2.0	1.1–2.9	1.7	1.2
14	PC_Petrol	Euro 2 Medium 1.4–2.0 l	1.5	0.5–2.6	2.1	1.9
15	PC_Petrol	Euro 2 Large-SUV-Executive > 2.0 l	1.3	0.4–2.3	1.9	1.5
16	HDV_Diesel	Euro IV Articulated 40–50 t SCR 40–50 t	1.5	0.8–2.3	1.5	1.0
17	LCV_Diesel	Euro 2 N1-III	1.5	0.8–2.2	1.4	0.8
18	HDV_Diesel	Conventional Articulated 40–50 t	1.3	0.7–2	1.3	0.7
19	PC_Petrol	Euro 3 Medium PFI 1.4–2.0 l	1.0	0.2–1.8	1.6	1.0
20	HDV_Diesel	Euro V Rigid > 32 t SCR > 30 t	1.2	0.6–1.7	1.2	0.6

As identified in Table 9.4, the priority emission technology classes in relation to the emissions of NO_x are LCV diesel vehicles built to Euro 4 or Euro 5 and petrol cars built to Euro 2 or lower.

9.2 NO_2

9.2.1 Vehicle class

The VEPM calculates NO_2 from NO_x by applying a conversion factor to the NO_x emission factor for each class of vehicle. The NO_2 conversion factor only applies to the in-exhaust pollutants and does not consider the atmospheric conversion. Priority ranking by vehicle class for NO_2 is shown in Table 9.5.

Table 9.5 Priority ranking by vehicle class for NO_2

Priority ranking	Vehicle class	RI (Eijv /Eij) (%)	RI confidence interval (lower limit–upper limit) (%)	Range confidence interval (%)	Uncertainty contribution to emission inventory (%)
1	LCV Diesel	52.4	36–62.1	26.1	87.3
2	Car Diesel	15.9	9.3–21.6	12.3	7.0
3	Car Petrol	7.5	2.1–12.4	10.2	4.1
4	HDV Diesel Articulated 34–40 t	3.3	1.6–4.8	3.2	0.4
5	HDV Diesel Articulated 40–50 t	2.4	1.2–3.6	2.4	0.2
6	HDV Diesel Articulated 28–34 t	2.3	1.1–3.4	2.2	0.2
7	HDV Diesel Rigid 3.5–7.5 t	2.2	1.1–3.3	2.2	0.2
8	Bus Diesel Urban 12–18 t	2.3	1.3–3.3	1.9	0.1
9	HDV Diesel Rigid > 30 t	2.1	1.1–3.1	2.1	0.2
10	HDV Diesel Articulated > 50 t	1.9	0.9–2.8	1.9	0.1
11	HDV Diesel Rigid 25–30 t	1.8	0.9–2.7	1.8	0.1
12	HCDV Diesel Rigid 20–25 t	1.6	0.8–2.3	1.5	0.1
13	HDV Diesel Articulated 20–28 t	1.2	0.6–1.8	1.2	0.0
14	HDV Diesel Rigid 10–20 t	1.1	0.6–1.7	1.1	0.0
15	LCV Petrol	1.0	0.4–1.6	1.2	0.0

As identified in Table 9.5, the priority vehicles classes in relation to the emissions of NO_2 are diesel LCVs, diesel cars, petrol cars and diesel HDVs heavier than 34 tonnes. The top three vehicle classes account for approximately 98% of the total uncertainty in the NO_2 UET (diesel cars 7%, diesel LCVs 87%, petrol cars 4%). The OAT analysis for NO_2 confirms that the rankings of all 15 vehicle classes are not sensitive to changes in emission factor sensitivity. The results of the OAT analysis demonstrate that the NO_2 ranking of priority vehicles is robust.

9.2.2 Emission technology

Priority ranking by vehicle class and emission technology for NO_2 is shown in Table 9.6.

Table 9.6 Priority ranking emission by technology class for NO_2

Priority ranking	Vehicle class	Emission technology	RI (Eijv /Eij) (%)	RI confidence interval (lower limit–upper limit) (%)	Range confidence interval (%)	Uncertainty contribution to emission inventory (%)
1	LCV_Diesel	Euro 5 N1-III DPF	23.1	13.3–30.9	17.6	59.9
2	LCV_Diesel	Euro 4 N1-III DPF	16.5	9.1–22.7	13.6	30.6
3	PC_Diesel	Euro 4 Large-SUV-Executive DPF > 2.0 l	6.2	3.4–8.8	5.3	3.7
4	PC_Diesel	Euro 4 Medium DPF < 2.0 l	3.4	1.8–4.8	3.0	1.1
5	LCV_Diesel	Euro 3 N1-III DPF	2.2	1.1–3.3	2.1	0.5
6	PC_Diesel	Euro 5 Large-SUV-Executive DPF > 2.0 l	2.3	1.2–3.3	2.0	0.5
7	HDV_Diesel	Euro IV Articulated 50–60 t SCR > 50 t	2.1	1–3.1	2.0	0.5
8	HDV_Diesel	Conventional Articulated > 50 t	1.5	0.7–2.2	1.5	0.3
9	HDV_Diesel	Euro IV Articulated 40–50 t SCR 40–50 t	1.4	0.7–2.1	1.4	0.2
10	LCV_Diesel	Euro 2 N1-III	1.3	0.7–2	1.3	0.2
11	PC_Petrol	ECE 15/04 Medium 1.4–2.0 l	1.1	0.5–1.6	1.1	0.1
12	PC_Diesel	Euro 1 Large-SUV-Executive J92, J94 > 2.0 l	1.1	0.6–1.6	1.0	0.1
13	PC_Diesel	Euro 3 Large-SUV-Executive DPF > 2.0 l	1.0	0.6–1.5	0.9	0.1
14	HDV_Diesel	Conventional Articulated 40–50 t	1.0	0.5–1.5	1.0	0.1
15	PC_Petrol	Euro 1 Medium J78, J88 1.4–2.0 l	0.8	0.3–1.4	1.1	0.1
16	HDV_Diesel	Euro IV Rigid > 32 t SCR > 30 t	0.9	0.5–1.4	1.0	0.1
17	HDV_Diesel	Euro IV Articulated 34–40 t SCR 34–40 t	0.9	0.4–1.3	0.9	0.1
18	HDV_Diesel	Euro III Articulated > 50 t	0.8	0.4–1.2	0.8	0.1
19	HDV_Diesel	Euro V Rigid > 32 t SCR > 30 t	0.8	0.4–1.2	0.8	0.1
20	PC_Petrol	Euro 1 Large-SUV-Executive > 2.0 l	0.7	0.2–1.1	0.8	0.1

As identified in Table 9.6, the priority emission technology classes in relation to the emissions of NO_2 are LCV diesel vehicles built to Euro 1 to 5 and large and medium-sized diesel cars built to Euro 1 to 5.

9.3 $PM_{2.5}$

9.3.1 Vehicle class

Priority ranking by vehicle class for $PM_{2.5}$ is shown in Table 9.7.

Table 9.7 Priority ranking by vehicle class for $PM_{2.5}$

Priority ranking	Vehicle class	RI (Eijv /Eij) (%)	RI confidence interval (lower limit–upper limit) (%)	Range confidence interval (%)	Uncertainty contribution to emission inventory (%)
1	LCV Diesel	40	22.9–50.6	28	73
2	Car Diesel	35	25.4–41.8	16	23
3	HDV Diesel Articulated 34–40 t	4	1–6.2	5	1
4	HDV Diesel Articulated 28–34 t	3	0.7–4.5	4	1
5	HDV Diesel Rigid 3.5–7.5 t	2	0.7–4.2	4	1
6	Bus Diesel Urban 12–18 t	2	0.8–4	3	0
7	HDV Diesel Rigid > 30 t	2	0.6–3.7	3	0
8	HDV Diesel Articulated > 50 t	2	0.5–3.2	3	0
9	HDV Diesel Rigid 25–30 t	2	0.5–3.2	3	0
10	HDV Diesel Rigid 20–25 t	2	0.4–2.9	2	0
11	Car Petrol	2	0.5–2.7	2	0
12	HDV Diesel Articulated 40–50 t	1	0.4–2.4	2	0
13	HDV Diesel Articulated 20–28 t	1	0.4–2.3	2	0
14	HDV Diesel Rigid 10–20 t	1	0.3–2	2	0
15	HDV Diesel Rigid 7.5–10 t	1	0.2–1	1	0

As identified in Table 9.7, the priority vehicles classes in relation to the emissions of $PM_{2.5}$ are diesel LCVs, diesel cars and HDV diesel articulated trucks. These three vehicle classes account for approximately 79% of the total fleet emissions for $PM_{2.5}$ (diesel cars 35%, diesel LCVs 40%, diesel articulated HDVs 4%). Light-duty diesel vehicles contribute to approximately 96% of total uncertainty, with other vehicle categories contributing 1% or less each. The OAT $PM_{2.5}$ analysis confirms the four top-ranked vehicle classes are not sensitive to changes in emission factor sensitivity. In ranks 5, 6 and 7, the vehicle classes swap their order. There is no change in the rankings of vehicle classes ranked 8 to 15. The results of the OAT analysis demonstrate that the $PM_{2.5}$ ranking of priority vehicles is robust.

9.3.2 Emission technology

Priority ranking by vehicle class and emission technology for $PM_{2.5}$ is shown in Table 9.8.

Table 9.8 Priority ranking emission by technology class for $PM_{2.5}$

Priority ranking	Vehicle class	Vehicle technology	RI (Eijv /Eij) (%)	RI confidence interval (lower limit–upper limit) (%)	Range confidence interval (%)	Uncertainty contribution (%)
1	LCV_Diesel	Conventional N1-III	11.6	11.4–11.9	0.4	8.6
2	PC_Diesel	Euro 1 Large-SUV-Executive J92, J94 > 2.0 l	5.0	4.7–5.3	0.5	11.0
3	LCV_Diesel	Euro 4 N1-III DPF	1.6	1–2.2	1.2	53.4
4	LCV_Diesel	Euro 2 N1-III	3.2	3–3.4	0.4	5.7
5	LCV_Diesel	Euro 3 N1-III DPF	2.3	2–2.5	0.5	9.9
6	LCV_Diesel	Euro 1 N1-III	3.1	3–3.2	0.2	1.2
7	PC_Diesel	Euro 1 Large-SUV-Executive J86 > 2.0 l	4.8	4.7–4.8	0.1	0.3
8	PC_Diesel	Euro 4 Large-SUV-Executive DPF > 2.0 l	1.0	0.9–1.2	0.3	3.7
9	LCV_Diesel	Euro 1 N1-III J88	3.1	3–3.1	0.1	0.2
10	LCV_Diesel	Euro 1 N1-III J97, J03	2.1	2–2.1	0.1	0.3
11	PC_Diesel	Euro 4 Medium DPF < 2.0 l	1.0	0.9–1	0.2	1.1
12	PC_Diesel	Conventional Large-SUV-Executive > 2.0 l	4.7	4.7–4.8	0.0	0.0
13	LCV_Diesel	Euro 1 N1-III J93	2.0	2–2.1	0.1	0.1
14	PC_Diesel	Euro 1 Large-SUV-Executive J98 > 2.0 l	2.5	2.5–2.5	0.0	0.1
15	PC_Diesel	Euro 1 Large-SUV-Executive > 2.0 l	2.5	2.5–2.5	0.0	0.1
16	PC_Diesel	Euro 3 Large-SUV-Executive DPF > 2.0 l	1.2	1.1–1.2	0.1	0.2
17	PC_Diesel	Euro 1 Medium J92, J94 < 2.0 l	4.7	4.7–4.8	0.0	0.0
18	PC_Diesel	Euro 2 Large-SUV-Executive > 2.0 l	1.5	1.4–1.5	0.0	0.1
19	PC_Diesel	Euro 3 Medium DPF < 2.0 l	1.2	1.1–1.2	0.0	0.0
20	PC_Diesel	Euro 1 Medium J86 < 2.0 l	4.7	4.7–4.7	0.0	0.0

As identified in Table 9.8, the priority emission technology classes in relation to the emissions of $PM_{2.5}$ are diesel LCVs built to Euro 3 or lower and low-technology diesel cars.

9.4 PM_{10}

9.4.1 Vehicle class

In the VEPM, PM_{10} is calculated as the emission of PM_{10} from the exhaust system plus a brake and tyre wear factor. Priority ranking by vehicle class for PM_{10} is shown in Table 9.9.

Table 9.9 Priority ranking by vehicle class for PM_{10}

Priority ranking	Vehicle class	RI (Eijv /Eij) (%)	RI confidence interval (lower limit–upper limit) (%)	Range confidence interval (%)	Uncertainty contribution (%)
1	LCV Diesel	30.8	10.1–43.8	33.6	64.0
2	Car Diesel	15.9	3.6–25.5	21.9	19.9
3	Car Petrol	19.1	10.1–26.5	16.3	12.1
4	HDV Diesel Articulated 34–40 t	4.5	1.8–7.2	5.4	1.0
5	HDV Diesel Articulated 28–34 t	3.4	1.3–5.3	4.0	0.5
6	HDV Diesel Articulated > 50 t	3.6	1.9–5.3	3.4	0.4
7	HDV Diesel Rigid > 30 t	3.4	1.7–5.1	3.5	0.4
8	HDV Diesel Rigid 3.5–7.5 t	3.1	1.2–4.9	3.7	0.4
9	Bus Diesel Urban 12–18 t	2.9	1.1–4.5	3.4	0.4
10	HDV Diesel Rigid 25–30 t	2.7	1.2–4.1	2.9	0.3
11	HDV Diesel Articulated 40–50 t	2.5	1.3–3.8	2.5	0.2
12	HDV Diesel Rigid 20–25 t	2.2	0.9–3.5	2.6	0.2
13	HDV Diesel Articulated 20–28 t	1.7	0.7–2.7	2.0	0.1
14	HDV Diesel Rigid 10–20 t	1.6	0.7–2.5	1.8	0.1
15	LCV Petrol	0.9	0.5–1.4	0.9	0.0

As identified in Table 9.9, the priority vehicles classes in relation to the emissions of PM_{10} are very similar to those identified for $PM_{2.5}$, mainly diesel LCVs and diesel cars. The key difference is the much higher ranking of petrol vehicles for PM_{10}, which reflects the relatively high influence of brake and tyre wear emissions for this vehicle class. The three top-ranked vehicle classes account for approximately 96% of the total uncertainty in the PM_{10} UET (diesel cars 20%, diesel LCVs 64%, petrol cars 12%). The OAT PM_{10} analysis confirms the four top-ranked ranked vehicle classes are not sensitive to changes in emission factor sensitivity. In ranks 5 to 9, the vehicle classes swap their order. There is no change in the rankings of vehicle classes ranked 10 to 15. The results of the OAT analysis demonstrate that the PM_{10} ranking of priority vehicles is robust.

9.4.2 Emission technology

An emission technology analysis was not undertaken for PM_{10} because the emissions of brake and tyre wear are not subject to an emission control technology.

9.5 CO_2

9.5.1 Vehicle class

Priority ranking by vehicle class for $PM_{2.5}$ is shown in Table 9.10.

Table 9.10 Priority ranking by vehicle class for CO_2

Priority ranking	Vehicle class	RI (Eijv /Eij) (%)	RI confidence interval (lower limit–upper limit) (%)	Range confidence interval (%)	Uncertainty contribution to emission inventory (%)
1	Car Petrol	57.1	55–59	4.1	32.6
2	LCV Diesel	15.3	9.8–20.1	10.3	53.4
3	Car Diesel	6.6	3.7–9.3	5.6	13.1
4	LCV Petrol	3.2	3–3.5	0.5	0.1
5	HDV Diesel Articulated 40–50 t	2.3	2–2.6	0.6	0.1
6	HDV Diesel Rigid > 30 t	2.0	1.7–2.2	0.5	0.1
7	HDV Diesel Rigid 3.5–7.5 t	1.9	1.6–2.2	0.5	0.1
8	HDV Diesel Articulated > 50 t	1.8	1.6–2.1	0.5	0.1
9	HDV Diesel Rigid 25–30 t	1.7	1.5–2	0.5	0.1
10	HDV Diesel Articulated 34–40 t	1.5	1.3–1.7	0.4	0.1
11	Bus Diesel Urban 12–18 t	1.5	1.3–1.7	0.4	0.1
12	HDV Diesel Rigid 20–25 t	1.2	1.1–1.4	0.3	0.0
13	HDV Diesel Articulated 28–34 t	1.2	1.1–1.4	0.3	0.0
14	HDV Diesel Rigid 10–20 t	0.9	0.8–1.1	0.3	0.0
15	HDV Diesel Articulated 20–28 t	0.6	0.6–0.7	0.2	0.0

As identified in Table 9.10, the priority vehicles classes in relation to the emissions of CO_2 are light-duty diesel and petrol vehicles. The three top-ranked vehicle classes account for approximately 99% of the total uncertainty in the CO_2 UET (diesel cars 13%, diesel LCVs 53%, petrol cars 33%). The OAT analysis for CO_2 confirms that the rankings of all 15 vehicle classes are not sensitive to changes in emission factor sensitivity. The results of the OAT analysis demonstrate that the CO_2 ranking of priority vehicles is robust.

9.5.2 Emission technology

Priority ranking by vehicle class and emission technology for CO_2 is shown in Table 9.11.

Table 9.11 Priority ranking emission by technology class for CO_2

Priority ranking	Vehicle class	Emission technology	RI (Eijv /Eij) (%)	RI confidence interval (lower limit–upper limit) (%)	Range confidence onterval (%)	Uncertainty contribution to emission inventory (%)
1	PC_Petrol	Euro 4 Medium PFI 1.4–2.0 l	7.4	6.8–7.9	1.1	25.4
2	PC_Petrol	Euro 3 Medium PFI 1.4–2.0 l	5.2	4.8–5.6	0.8	17.1
3	LCV_Diesel	Euro 4 N1-III DPF	7.7	7.4–7.9	0.5	8.2
4	PC_Petrol	Euro 1 Medium J78, J88 1.4–2.0 l	4.4	4.1–4.8	0.7	8.5
5	PC_Petrol	Euro 4 Medium J05 1.4–2.0 l	4.2	3.9–4.6	0.7	4.9
6	PC_Petrol	Euro 4 Large-SUV-Executive PFI > 2.0 l	4.1	3.8–4.4	0.6	3.1
7	PC_Petrol	Euro 5 Medium PFI 1.4–2.0 l	4.0	3.7–4.3	0.6	2.0
8	PC_Diesel	Euro 4 Large-SUV-Executive DPF > 2.0 l	1.5	0.7–2.3	1.5	2.4
9	PC_Petrol	Euro 3 Large-SUV-Executive PFI > 2.0 l	3.9	3.6–4.2	0.6	2.6
10	LCV_Diesel	Euro 5 N1-III DPF	5.2	5–5.3	0.3	2.2
11	PC_Petrol	Euro 3 Medium J00 1.4–2.0 l	3.0	2.8–3.3	0.5	1.7
12	PC_Diesel	Euro 4 Medium DPF < 2.0 l	1.1	0.6–1.5	0.9	1.4
13	PC_Diesel	Euro 5 Large-SUV-Executive DPF > 2.0 l	0.9	0.4–1.3	0.9	2.3
14	PC_Petrol	Euro 2 Medium 1.4–2.0 l	2.1	1.9–2.3	0.3	1.2
15	PC_Petrol	Euro 4 Large-SUV-Executive J05 > 2.0 l	2.0	1.8–2.2	0.3	1.8
16	PC_Diesel	Euro 1 Large-SUV-Executive J92, J94 > 2.0 l	0.7	0.3–1.1	0.7	0.8
17	PC_Petrol	Euro 5 Large-SUV-Executive PFI > 2.0 l	1.7	1.6–1.9	0.3	0.7
18	PC_Petrol	Euro 3 Large-SUV-Executive J00 > 2.0 l	1.4	1.3–1.5	0.2	1.2
19	PC_Petrol	Euro 2 Large-SUV-Executive > 2.0 l	1.3	1.2–1.5	0.2	0.6
20	PC_Petrol	Euro 1 Medium 1.4–2.0 l	1.3	1.2–1.4	0.2	0.6

As identified in Table 9.11, the priority emission technology classes in relation to the emissions of CO_2 are large or medium-sized petrol cars built to Euro 1, 3 or 4 and LCV diesel vehicles built to Euro 4.

9.6 Summary of findings

This chapter has identified priority vehicles types that have both relatively large:

- impact (significant contribution to total emissions)
- uncertainty in estimated emissions.

A summary of the top-ranking vehicle classes for each key pollutant is given in Table 9.12. In general, LDVs, both private and commercial, have the highest uncertainty in the fleet contributions, mainly due to the large proportion of these vehicles in the New Zealand fleet, resulting in a large RI to overall emissions. The exception to this trend is for $PM_{2.5}$, where HDVs diesel do rank within the top three, but with just 1% uncertainty contribution.

Table 9.12 Summary of top-ranking vehicle classes for each pollutant

Rank	CO_2	NO_2	NO_X	PM_{10}	$PM_{2.5}$
1	Car Petrol	LCVs Diesel	Cars Petrol	LCVs Diesel	LCVs Diesel
2	LCV Diesel	Cars Diesel	LCVs Diesel	Cars Diesel	Cars Diesel
3	Car Diesel	Cars Petrol	Cars Diesel	Cars Petrol	HCVs Diesel Articulated 34–40 t

Given that NO_x and NO_2 diesel vehicle emission factors are significantly higher than those of petrol vehicles, it might be considered counterintuitive to see petrol passenger cars featuring in the top three vehicle classes for these two pollutants. On a vehicle-by-vehicle comparison, diesel vehicles have a higher NO_x and NO_2 impact than petrol vehicles. However, this study is examining the fleet-wide impacts of vehicle types on total emissions. In the fleet-wide context, there are many more petrol vehicles and together, they travel a greater distance than diesel vehicles, which means petrol vehicles have a greater impact on total emissions. Therefore, when vehicle activity data is factored into the equation for total emissions, petrol vehicles rank in the top three vehicle classes for NO_x and NO_2.

To enable the design of targeted emission monitoring, the priority vehicle types were binned by emission technology and vehicle size/weight. These two pieces of information were used to assist the design of future vehicle emission and fuel use measurement programmes (see Chapter 10).

10 Filling emission and fuel use knowledge gaps

This chapter examines the range of methods available regarding vehicle emission measurement and discusses the strengths and weaknesses of each method, as well as its applicability in the New Zealand context. The chapter:

- reviews the monitoring method options (PEMS, RSD, dynamometer, roadside air quality monitoring, etc); considers their costs, value and practicalities
- explicitly links the design of potential new programmes for vehicle emission monitoring with the knowledge gaps and priority vehicle types that were revealed earlier
- recommends appropriate programmes for emission and fuel use monitoring.

10.1 Monitoring methods

A substantial part of the following discussion has been sourced from review studies (Ropkins et al., 2009; Smit et al., 2009; Smit et al., 2010; Smit & Somervell, 2015) but they are not referenced further in this section for readability reasons and because of significant overlap in the information they each provided.

Emission models are developed from emission measurements and several different emission measurement methods are available, such as laboratory engine bench testing, laboratory chassis dynamometer testing, on-board measurements, near-road measurements and tunnel studies.

A review study by Smit et al. in 2010 identified six monitoring methods that can be employed at different spatial scales (local, road, journey, area). Table 10.1 presents an overview of the general features that are typical for each of these methods. Further details are provided in the following sections, which also consider two methods that have emerged more recently: on-road vehicle plume measurement and on-board sensors.

Table 10.1 Methods of monitoring vehicle emissions – general features (reprinted from Smit et al., 2010, p. 2945)

Measurement technique	Subject of comparison	Input data[a]	Spatial features	Temporal features	Driving conditions
Laboratory	Emission factor [g veh km^{-1}]	Measured (100%)	Urban journey, no gradient effects included.	Resolution: typically 10 minutes (representing urban journey for one vehicle), with total sampling time of about 35 hours.	Both urban and motorway traffic conditions.
On-board	Emission factor [g veh km^{-1}]	Measured (100%)	Urban journey, road gradients of −4% to +5% included in the driving patterns (Silva et al., 2006).	Resolution: typically 4–14 minutes (representing urban journey), with total sampling time of several days.	Both urban and motorway traffic conditions.
Tunnel	Emission factor [g veh km^{-1}]	Measured (100%)	Section of road with lengths varying from a few hundred meters (Ingalls, 1989) to 10 km (Hausberger et al., 2003). Several studies done in tunnels with significant road gradients up to 4.2% (Kirchstetter et al., 1996).	Resolution: typically one hour averages, but total sampling times vary from 10 hours (Hwa et al., 2002) to a month (Colberg et al., 2005a).	Mainly high-speed, free-flowing traffic.
Remote sensing	Emission factor, Total Emissions [g veh km^{-1}, g kg^{-1} fuel]	Measured (100%)	Several locations, varying from 3 (Ekström et al., 2004) to 35 (Singer and Harley, 2000). Locations typically with slight or significant road gradients (up to 5%) (e.g. Singer and Harley, 1996)	Resolution: typically less than one second, and sampling times vary from 36 days (Singer and Harley, 2000) to 7 months (Guo et al., 2007).	Both urban and motorway traffic conditions.
Ambient concentration	Concentration [μg m^{-3}]	Measured (50%), Modelled (50%)	Typically one location only, but a few studies used more locations (2–3) up to 12 (Peace et al., 2004) and 31 locations (Mensink et al., 2001).	Resolution: typically one-hour averaged values, but total sampling times vary from a few hours (Negrenti, 1998; Vogel et al., 2000) to a full year (Namdeo et al., 2002; Peace et al., 2004).	Mainly urban locations.
Mass-balance	Emission flux [kg h]	Modelled (100%)	Urban areas of 10 × 10 km^2 (Panitz et al., 2002) to 20 × 20 km^2 (Mensink, 2000).	Resolution: typically 1 hour with total sampling time of a few hours.	Both urban and motorway traffic conditions.

[a] Traffic volume, speeds, fleet composition.

Vehicle emission testing at the time of warrant of fitness and certificate of fitness checks (in-service testing) was initially considered a potential method of collecting data that could be used to fill the knowledge gaps identified in Chapter 9. However, this testing method was found to have several drawbacks, which resulted in it being discounted from the vehicle-monitoring methods considered. The drawbacks were as follows:

- The data collected does not necessarily represent real-world driving conditions.
- It is generally accepted that opacity testing for diesel vehicles is a poor predictor of on-road PM emissions.
- It would require significant work to overcome the logistics issues and industry inertia involved in setting up a network of vehicle emission test facilities for a programme that is not mandated by any regulations.
- There would be significant costs involved in the purchase, installation, commissioning, maintenance and operation of the network of monitoring equipment.
- The in-workshop emission-testing equipment has limitations (Boulter et al., 2011).
- Technicians/mechanics would have to be trained to undertake the tests and record the data.
- The quality of the data collected by workshop emission-testing equipment is relatively poor.

10.1.1 Laboratory measurement

Laboratory vehicle exhaust emission testing (see Figure 10.1) involves a chassis or engine dynamometer and predefined drive cycles. Laboratory testing is required for standardised vehicle emissions measurement (eg emissions legislation, engine manufacture guidelines, technology development). However, the need for reproducibility is not necessarily a requirement for vehicle emission (inventory) models. Nevertheless, most emission models have traditionally been based on laboratory emission testing, using engine or vehicle dynamometers and predefined test or driving cycles. In fact, the non-laboratory methods that are discussed later in this chapter seem to have evolved from independent emission model validation studies for laboratory-based testing models, to create credible empirical databases for emission model development and maintenance.

Figure 10.1 Laboratory emission-testing set-up (reprinted from Orbital, 2009, p. 37)

Laboratory vehicle exhaust emission testing may be conducted using Tedlar sample bags that are analysed after completion of the driving cycle, or by using continuous measurement at a high time resolution (typically 1–10 Hz). As it is the method prescribed by emission legislation around the world, bag sampling has traditionally been the dominant approach. Therefore, a large body of bag test data is available and these data have traditionally been used in the development of emission models. The second method – continuous (modal) measurement – has become increasingly common over time for emission rate calculation and engine development. It involves some additional issues, such as correction for the time lag and mixing dynamics in the sampling and analysis system, before the measured emission values can be correctly correlated with driving conditions.

Laboratory measurements were traditionally based on standard (vehicle) driving or (engine) test cycles (eg Federal Test Procedure, New European Drive Cycle, European Transient Cycle) but over time, they have come to include cycles that better reflect real-world driving conditions ('off-cycle') and therefore, emissions (eg Common Artemis Driving Cycles, Australian Urban Cycle). Indeed, the EU adopted a new test procedure in 2017, the Worldwide Harmonized Light-duty Test Procedure, to address the increasing gap between on-road emission tests and the legislative New European Drive Cycle test procedure (Fontaras et al., 2014). This gap can be large for individual vehicles, even exceeding an order of magnitude in some cases (International Council on Clean Transportation, 2017). Although the US uses different test procedures from the ones used in Europe, they also suffer from an increasing gap between the official (2-cycle) Federal Test Procedure test and real-world emissions. The US already uses a 5-cycle test to better estimate real-world fuel use and emissions. The 5-cycle test is expected to be a reasonable approximation of US real-world fuel efficiency and CO_2 emission rates, and it may even be slightly conservative (US Environmental Protection Agency, 2019). It is likely that the use of standard test cycles like the New European Drive Cycle in the development of emissions models will lead to significantly biased emission models (underestimation), and this should be prevented.

An advantage of laboratory measurements is that they are conducted under controlled conditions. This enables investigation of specific aspects such as driving pattern, hot-running/cold-start conditions, vehicle loading, use of air conditioning, ambient temperature and emission control technology. These measurements are also flexible in terms of spatial and temporal resolution. Emission results can be expressed, for example, as g/km, g/s, g/mode and g/kg fuel. In addition, laboratory measurements are amenable to a broad range of sampling methods and instrumentation.

A disadvantage of this method is the limitation on the number of vehicles or engines that can be tested due to time and budget constraints. This is a weakness because a significant sample size is required to capture the variability in real-world vehicle emissions. There are also concerns of potential sampling bias in laboratory programmes, as owners of 'high emitters' have been reported to be reluctant to (voluntarily) submit their vehicles for testing. High emitters have excessive emissions due to malfunctioning equipment (eg less-robust emission controls, neglect of maintenance), intentional tampering or faulty repairs. In addition, emissions from high-emitting vehicles are more variable than emissions from normal emitters and thus, require a large sampling fraction to obtain reasonably accurate emission estimates. Therefore, models based on laboratory test data alone are potentially biased and may significantly underestimate traffic emissions.

Another point of concern is how well on-road conditions are replicated by the test equipment, such as dynamometer settings and dilution conditions. Correlation studies are therefore important to clarify the differences between the monitoring methods.

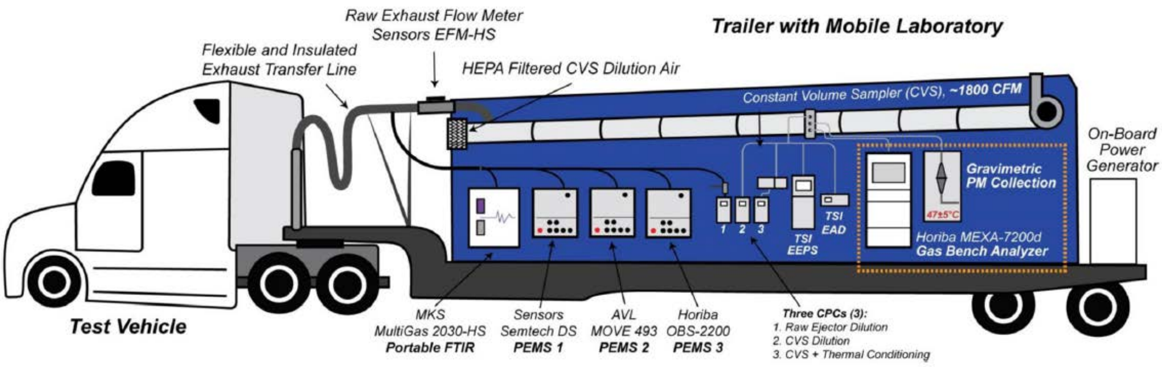
10.1.2 On-board measurement (PEMS, Mobile Emissions Laboratory, Transportable Emissions Measurement System)

On-board measurement has become a popular method of providing detailed and reliable emissions data for a range of vehicle classes. On-board emission measurement systems range from compact PEMS (see Figure 10.2) to elaborate configurations (see Figure 10.3). An example of the latter is the mobile Constant Volume Sampling laboratory (Mobile Emissions Laboratory or Transportable Emissions Measurement

System), which can be affixed to a flatbed trailer along with an on-board power generator and other emissions measurement equipment (Quiros et al., 2017).

Figure 10.2 PEMS emission-testing set-up for LDVs (reprinted from Weiss et al., 2011, p. 8575)

Figure 10.3 PEMS emission-testing set-up for HDVs (reprinted from Quiros et al., 2016, p. 158)



PEMS testing (see Figure 10.2) was not traditionally used in the development of traffic emission models but this has changed, as discussed previously. Compared with laboratory testing, this method provides reasonable control over influencing factors (eg cold-start, vehicle loading). However, testing a large vehicle sample is still restricted by labour time, effort and costs, particularly for older vehicles that require more set-up time, as relevant operational data may not be extracted readily from the engine management system.

Of note is the development of lower-cost and simplified PEMS to evaluate real-world emissions performance in a simple yet robust way. The terminology varies, but mini-PEMS or smart emission measurement systems have been used. For instance, Vermeulen et al. (2012) developed a smart emission measurement system that combined an automotive NO_x and oxygen sensor and a GPS tracker.

Another 'derived' application is the low-cost Portable Activity-Monitoring System (PAMS), which is essentially a reduced version of PEMS, able to measure some critical vehicle operation parameters from the electronic control unit, such as vehicle/engine speed, engine load, lamda sensor signal, engine coolant temperature, intake air and GPS position (Rubino et al., 2007).

10.1.3 Tunnel measurement

The tunnel measurement method is well established for validating vehicle emission models at the fleet level (see Figure 10.4). Tunnel studies repeated over time can be useful for trend analysis of fleet-averaged emission factors. With this method, composite emission factors are determined using the differences in pollutant concentrations at the tunnel entrance and exit (corrected for background concentrations), combined with tunnel features (eg road length, cross-sectional area), traffic flow and traffic conditions, as well as either measured tunnel air flow or dilution factors based on a tracer gas (eg SF_6).

Figure 10.4 Concentration measurements within tunnel ventilation system (reprinted from Smit et al., 2017, p. 190)

Regression analysis is often used to develop mean emission factors (g/km) for basic vehicle classes (eg LDV, HDV). License plate information is typically recorded to obtain a detailed breakdown of the on-road fleet. In tunnels with distinct traffic flow patterns (eg separate bores for trucks), separate emission factors can be obtained directly.

Tunnel studies measure emissions from a large sample of the on-road fleet, thereby adequately capturing inter-vehicle variability in emissions, including high emitters. Moreover, measurements are carried out under relatively controlled conditions. For instance, the air dilution conditions are better known in tunnels than in open-road experiments, and the influence of meteorological parameters is usually negligible. Also, the dispersion of pollutants is constrained by the geometry of the tunnel. A wide range of measurement instruments can be applied readily in road tunnel studies.

However, the tunnel method relies on indirect estimation rather than direct exhaust measurement, and this can introduce errors. Moreover, it captures only a limited range of operating conditions (typically smooth, uncongested, high-speed driving) and may induce a bias due to uphill or downhill gradients. Finally, the so-called 'piston effect' (which occurs with one-way traffic flow) and any forced ventilation in the direction of the traffic flow may combine to produce an effective tail wind that reduces aerodynamic drag on the vehicles in the tunnel. The effects of these on emissions can be substantial.

Other limitations of the tunnel method include assumptions relating to the proportion of vehicles in cold-start mode, unrecognised vehicles and vehicle loading. For PM, an additional problem arises from the contribution to total concentrations of both exhaust and non-exhaust sources; the latter include tyre and brake wear, road dust re-suspension and even direct emissions, such as those from gravel trucks.

10.1.4 Remote sensing

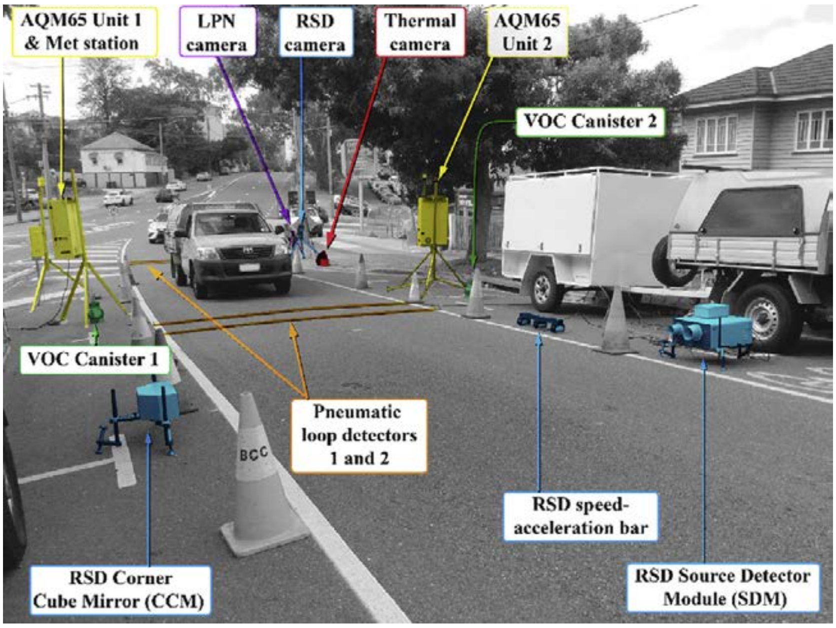
Remote sensing is well established. It uses open-path instruments at a fixed location where the absorption of IR/UV light by ambient air pollution across the road is used to measure pollutant-to-CO_2 ratios with wave-length specific detectors for different air pollutants (see Figure 10.5). While remote sensing permits the direct 'snapshot' (< 1 second) measurement of emissions from large vehicle samples, which is a clear advantage, it can produce a significant amount of invalid data. RSD measurements may also exclude relevant vehicle types and traffic conditions, depending on the RSD set-up (eg a truck with a vertical exhaust pipe measured with a ground-based set-up). However, scaffolding can be used with multiple RSDs to measure emissions at various heights.

Remote sensing provides a location-specific 'transect' snapshot of emissions under certain speed and acceleration conditions. There is, for instance, a tendency for invalid readings in particular traffic situations (eg low engine power conditions, congested conditions). The resulting emission factors are commonly expressed as pollutant-to-CO_2 concentration ratios or converted to fuel-based emission factors (g/kg fuel). This obviously differs from the distance-based emission factors (g/km) from laboratory measurements, PEMS or tunnel measurements, which are usually averaged over a range of driving conditions. Remote sensing concentration ratios can be converted to emission factors expressed as g/km or g/s by using estimates for g CO_2/km or g CO_2/s (fuel consumption) for each vehicle class (eg Ghaffarpasand et al., 2020; Smit & Somervell, 2015).

Compared with other monitoring methods, remote sensing is typically restricted to a limited number of air pollutants (or rather, ratios). Conventionally, CO, Total Hydrocarbons (THC), CO_2, NO and 'smoke' (an indicator for 'soot') were measured but more recently, NO_2, NH_3, SO_2 and N_2O have been added. Remote sensing has a lower sensitivity and higher level of noise than laboratory/PEMS measurements, so accurate detection of low concentration levels could be an issue because most modern vehicles typically exhibit low emission levels. Further, differences in measurement techniques need to be considered and accounted for (although this applies generally to all monitoring methods). For instance, a (constant) scaling factor is used to convert NDIR-based measurements (remote sensing) to approximately 'flame ionisation detector (FID)-equivalent' (laboratory) THC concentrations.

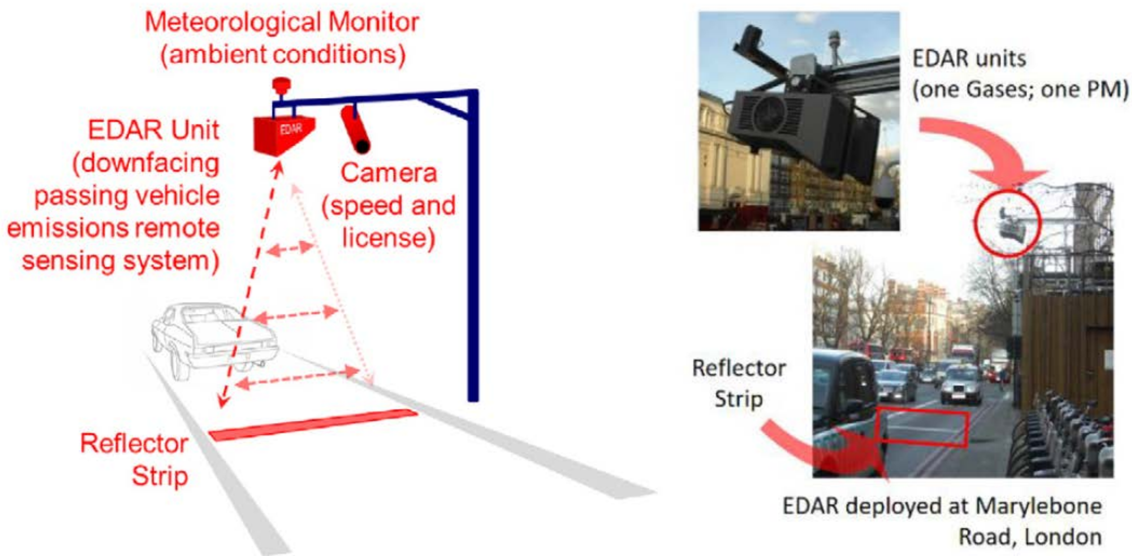
RSD measurements can be augmented by co-locating other measurement devices such as (mobile) integrated air quality monitoring stations, VOC canisters, loop detectors, a second license plate number camera, a thermal camera (see Figure 10.5) and Bluetooth MAC address units. This set-up can improve the capture rate and provide additional information that is useful in the analysis of emissions, such as the proportion of hot-running/cold-start vehicles.

Figure 10.5 Augmenting remote sensing measurements with additional equipment (reprinted from Smit et al., 2019, p. 3)



An alternative to conventional remote sensing is the above-road Emission Detection and Reporting (EDAR) system (see Figure 10.6). This system uses a patented variation of the Differential Absorption LIDAR technique, which could offer greater sensitivity and granularity than conventional remote sensing. For instance, it can be set up to measure individual VOCs. The downward-facing camera configuration above the road can have additional advantages, such as being less disruptive to traffic flow and less susceptible to system fouling, as well as providing continuous measurements over longer periods. The system has been used in the UK (Ghaffarpasand et al., 2020).

Figure 10.6 EDAR system (reprinted from Ropkins et al., 2017, p. 1466)



10.1.5 Near-road plume measurements (air quality)

This method collects near-road ambient concentration data at fixed near-road locations or points. The scientific literature can be somewhat confusing when it refers to 'mobile platform measurements', which can be either fixed-location (ie mobile but stationary) plume concentration measurement (the subject of this section of this document) or on-road moving vehicle plume measurement (the subject of the next section). In fact, some studies have used both approaches. Stationary near-road plume measurements can:

- either directly compare measured (near-road) ambient pollutant concentrations with the results from combined emission and (line source) dispersion/chemistry modelling (including background concentrations)
- or back-calculate emission factors through the inverse modelling of dispersion (ie dispersion or dilution factor) and taking into account local traffic and meteorological conditions.

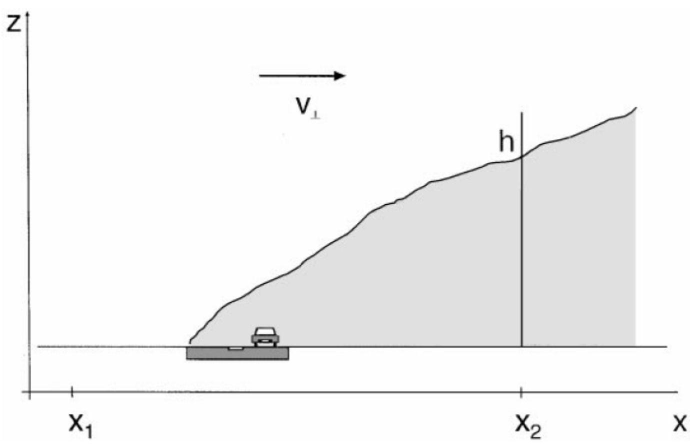
This method is mobile (ie easy to set up at different locations), and it can potentially capture a range of driving conditions with a large vehicle sample, both of which are advantages for vehicle emission monitoring. However, the combined use of both emission and dispersion models, and the impacts of non-traffic emission sources and simplifications (such as perfect mixing or steady-state wind conditions) introduces additional uncertainty. In addition, meteorological conditions (eg wind speed and direction) cannot be controlled but they need to be within certain thresholds to enable the collection of useful data. This can significantly affect the data capture rate. Further, it is assumed that chemical transformations and other processes (eg deposition, particle coagulation) are negligible when compared with the impact of dilution processes, and they can be ignored. Therefore, the method works best with relatively inert air pollutants such as CO and NO_x, and it is less appropriate for chemically reactive pollutants such as NO and NO_2.

Monitoring is typically restricted to one or a few specific location(s) in a road network (eg junction, mid-block). The location of the monitoring equipment is important, as emissions and concentrations are not evenly distributed along a road; for instance, they can have elevated levels near junctions. Therefore, validation based on a single measurement site may be particularly prone to errors, and these measurements may not compare well with distance-based emission factors. Average values from several measurement sites along a road, or from different points on the network, would give higher confidence, but this is rarely done.

An alternative approach that is less sensitive to site selection is to normalise ambient concentration measurements for CO_2 (or estimated fuel consumption), similar to remote sensing, and to compute emission ratios or use air pollutant ratios.

Another approach using ambient concentration data is a mass-balance study. Here, emission mass fluxes (kg/h) are determined through the measurement of pollutant concentrations upwind and downwind of specific roads/areas at different heights using, for example, aircraft or masts, and then comparing these data with emission predictions calculated by the emission model during the same period (see Figure 10.7). The issues are similar to those discussed for emission/dispersion/chemistry modelling. Another consideration is whether the different measurement heights adequately capture the plume and changes in concentration fluxes. Trace gases can be used to validate the measurement set-up.

Figure 10.7 Mass-flux concept (reprinted from Vogel et al., 2000, p. 2438)



In fact, some studies have used tracer gases directly to estimate emission factors from concentration measurements. For instance, Belalcazar et al. (2010) used a 100 m hose that emitted tracer gas continuously at a constant rate and at the same time, measured concentrations at the other side of the street. These data were used to compute dispersion factors to link ambient concentration data to traffic counts and emission factors.

Another approach is to capture (truck) exhaust plumes above the road (on an overpass) at a high resolution (1 Hz) and estimate fuel-based emission factors (g/kg) using the carbon balance approach for 4- to 10-second time windows with plume capture. Dallmann et al. (2011) used this approach to assess the impacts of an accelerated DPF retrofit and truck replacement programme at the Port of Oakland, California (see Figure 10.8).

Figure 10.8 Above-road HDV emissions monitoring (reprinted from Dallmann et al., 2011, p. 10774)

Finally, another variation is the use of an exhaust collection-and-containment system (ie a large tent) to capture vehicle emissions and measure pollutant concentrations (see Figure 10.9). This approach is a hybrid of remote sensing and near-road ambient concentration measurements. Bishop et al. (2015) used this approach to measure the fuel-based emission factors (g/kg) of thousands of trucks in the Port of Los Angeles, California. The key advantage of this system over remote sensing is the collection of PM emissions, as well as collection of additional information such as vehicle mass (using a weigh station).

Figure 10.9 On-road system for HDV emissions monitoring (reprinted from Bishop et al., 2015, p. 1639)

As a final comment, the measurement of near-road air quality is useful in its own right. It can be used, for instance, to assess trends or in source-apportionment studies (Harrison et al., 2011).

10.1.6 On-road vehicle plume measurements

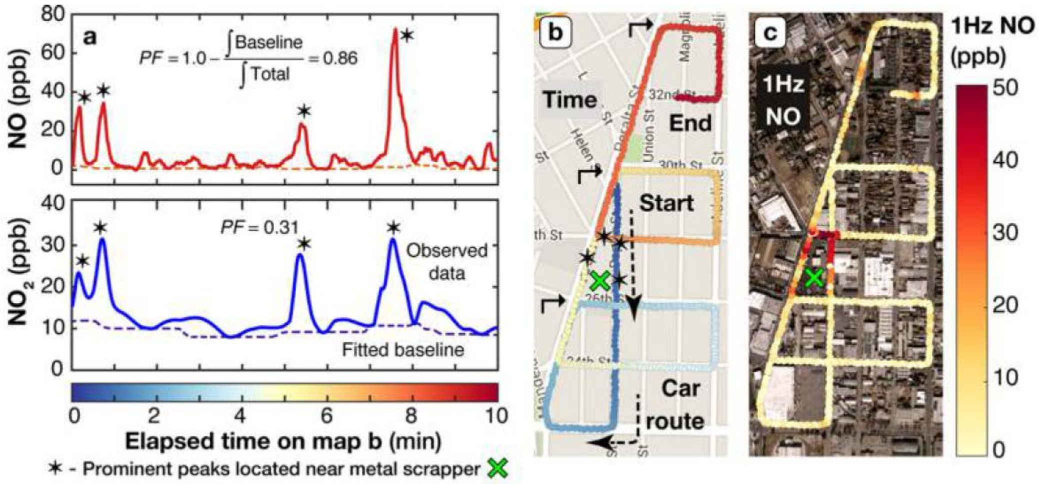
In this approach, a measurement vehicle (often referred to as a 'mobile platform' or 'sniffer') chases a target vehicle and monitors the ambient air on the road while driving, using conventional inlet systems located away from the measurement vehicle's own exhaust system (eg radiator grille, air conditioning/ventilation air intake). Specific vehicles are selected to be the chased vehicle, which is followed directly by the measurement vehicle for a given period in actual traffic conditions (see Figure 10.10). Alternatively, the measurement vehicle can be driven in traffic that is following 'general' driving behaviour and the on-road concentrations that are measured are assumed to result from general vehicle (fleet) emissions. Sometimes, both approaches are used.

Figure 10.10 Exhaust plume measurement test (reprinted from Pirjola et al., 2004, p. 3628)

As with remote sensing, emission ratios (ambient pollution concentrations normalised to CO_2 concentrations or fuel consumption) rather than emission factors (eg g/km, g/s) are often the statistic of interest, although some studies have reported only concentrations, or have used dilution ratios to estimate emission factors.

It is noted that measuring on-road air quality is useful in its own right. In some studies, a vehicle has been instrumented and ambient concentrations have been measured at a high resolution while driving over a predefined route (eg Bukowiecki et al., 2002). The main difference from on-road vehicle plume measurements was that the focus was on ambient concentration data, general air quality surveying and assessing variability in concentration levels in time and space. In another example, Apte et al. (2017) instrumented Google Street View cars with fast-response (1 Hz) laboratory-grade concentration measurement equipment and sampled every street in a 30 km^2 city area for more than a year. The data were then used to identify pollution hot spots and interpreted to better understand the main causes of locally elevated pollutant concentrations (see Figure 10.11).

Figure 10.11 Air pollution mapping using instrumented vehicles (reprinted from Apte et al., 2017, p. 7005)



The strength of on-road plume measurements is their ability to measure emissions in a range of unrestricted real-world traffic conditions at a high resolution. It can also capture exposure-relevant PM, reflecting the rapid changes in 'fresh' PM emission from the exhaust (eg cooling/condensation, nucleation, secondary PM). However, collecting detectable plumes from individual vehicles can be a challenge, as exhaust plumes dilute very fast. This is a particular issue for vehicles with the latest technology – it can be difficult to distinguish vehicle emissions from background levels of pollutants. In addition, reliable estimation of background pollutant concentrations may be difficult in specific traffic situations, such as congested urban traffic.

As an alternative approach, Sun et al. (2014) deployed open-path sensors on the roof of a car (mobile platform) and computed fuel-based emission factors by comparing slow (background) and rapid (plume) changes in concentrations and deriving emission ratios, such as $\Delta NH_3/\Delta CO_2$ (see Figure 10.12), while driving on the road.

In terms of sampling periods, on-road plume-chasing methods can be deployed to measure the emissions from a vehicle for several minutes. This method sits somewhere between remote sensing (< 1 second) and PEMS (entire journeys). More recently, on-road plume chasing has been tested and recommended as a low-cost, efficient approach for the identification of high emitters, such as trucks with SCR emulators (Pöhler et al., 2019).

Figure 10.12 Open-path sensors on vehicle roof (reprinted from Sun et al., 2014, p. 3943)

10.1.7 On-board sensors

The use of on-board sensors is a less complex application of the on-board measurements discussed earlier.

In this approach, critical vehicle operation parameters are collected from the electronic control unit and on-board sensors to estimate a vehicle's in-use emissions. An example is the collection and use of SCR sensor data through the Controller Area Network for NO_x emissions estimation (Kotz et al., 2016). This could be a more cost-effective and efficient approach than laboratory or PEMS testing in providing comprehensive feedback about in-use NO_x emissions. However, the validity of this approach depends on the presence and accessibility of on-board sensors in on-road vehicles, the quality of measurements (sensitivity, accuracy, faulty sensors), and the ability to capture all driving conditions (eg cold-start) and the range of pollutants. Nevertheless, this approach is certainly attracting attention in the US and the EU, also in the light of monitoring and reporting of real-world fuel use and CO_2 emissions using, for example, wireless in-use data transmission.

10.1.8 Conclusions

Each monitoring technique has its own strengths and weaknesses, and there is no golden bullet. The main aspects that should be considered are as follows:

- **Research objective**: Methods have specific strengths that can shortlist the potential monitoring methods when the research objective is considered. For instance, technology impact assessment (eg retrofit) requires a method that is accurate and can assess a range of situations (congestion, cold-start, ambient temperature, etc); laboratory and on-board PEMS would be well suited for this. In contrast, remote sensing, ambient concentration measurements and tunnels studies are useful for independent vehicle emission model validation or the development/verification of particular algorithms (eg use of RSDs for the impacts of vehicle ageing).
- **Pollutants**: Some methods (laboratory, tunnel, ambient concentration and, to a lesser extent, use of on-board sensors) can readily include a full range of monitoring equipment and therefore, are well suited to estimate emissions for a wide range of air pollutants and GHGs. Other methods (remote sensing, car plume) have limitations in the amount and type of monitoring equipment that can be used.
- **Spatial/temporal scale**: Laboratory, car plume and on-board sensor methods are strong on this aspect, as they are measured at a high resolution, leading to a flexible expression of emission factors varying

from instantaneous 1 Hz emission factors (g/s) to journey-based emission factors (g/km), and any scale in between. Remote sensing, ambient concentration and tunnel measurements are typically restricted to a particular location, or a few locations at best.

- **Real-world emissions**: It is important to reflect real-world emission levels and their variability in vehicle emission factors. On-board sensor and car plume studies appear particularly strong on this aspect, whereas laboratory measurements may be weakest on this aspect (even with real-world drive cycles). Other methods would generally capture real-world emissions, but they often have restrictions in terms of locations feasible for measurements (tunnel studies, remote sensing, ambient concentration), which could affect the representativeness of the emission measurements.
- **Sample size**: Some methods are clear winners in terms of sample size, such as tunnel studies, remote sensing and ambient concentration measurements. Laboratory, PEMS, car plume and on-board sensor measurements are limited in sample size due to resource and cost constraints.
- **Emission types**: Laboratory measurements and PEMS are capable of specifically measuring and distinguishing between different types of emissions (hot-running/cold-start, evaporative emissions, non-exhaust PM), whereas others would include a mix of them (tunnel studies, remote sensing, plume methods) or would be limited (on-board sensors).

Finally, using the same test vehicle(s) with multiple methods is useful for assessing the level of correlation between the test methods and establishing linkages between emission data sets (eg Dixit et al., 2017; Smit & Kennedy, 2020; Woo et al., 2016; Yang et al., 2018).

10.2 Criteria for choosing new methods of emission and fuel use monitoring in New Zealand

The recommendations (in Section 10.4 of this report) for new studies on emission and fuel use monitoring studies in New Zealand are based on a review of the criteria set out in this section of the report. Recommendations for Stage 2 of this project, based on these criteria, are presented in Section 10.4.

10.2.1 Research objectives of Phase 2 of the project

The research objectives of Phase 2 are to:

- fill the priority emission and fuel use knowledge gaps as identified in Phase 1 of the project
- improve the real-world representativeness of the VEPM.

10.2.2 Pollutants

The key health impacts pollutants identified by this study are $PM_{2.5}$, PM_{10} and NO_2. It is recommended that all these pollutants be included in any future studies on vehicle emission monitoring. The relative health impact of these pollutants on the population is assessed by the *Health and Air Pollution in New Zealand* study (Ministry for the Environment, 2012); this could be used, if required, to assess which pollutants have the most impact on population health and to set a priority on monitoring that pollutant.

CO_2 has been identified as the key GHG to be monitored and is the key marker of fuel use.

10.2.3 Spatial/temporal scale

The VEPM provides fleet average emission rates on a g/km basis. To maximise its utility, VEPM outputs emission rates can be varied according to vehicle speed and road slope, among other modifiers. In the real world, slope and speed vary significantly at a high spatial and temporal resolution.

Averaging and aggregation will typically result in lower levels of uncertainty than situations with higher levels of detail – for example, an hourly versus annual temporal consideration, or the individual link level versus the whole of New Zealand as the spatial scale. For instance, total vehicle daily emissions on a particular road may be relatively stable over weekdays and the uncertainty analysis would focus on sources of variation that affect daily emissions. In contrast, emissions over short periods (say, hourly) would be more uncertain and would need to consider the sources of variation that affect the wider range of possible values at hourly levels.

Phase 2 measurements should reflect this variability.

10.2.4 Real-world emissions

To fulfil the key objectives of the Phase 2 project, it is considered essential that emissions and fuel use are measured in real-world conditions, not using vehicle emissions data that cannot be considered to contain real-world aspects (eg New European Drive Cycle emission test data). On-road or near-road emissions testing is particularly useful.

10.2.5 Sample size

Reducing uncertainty in the VEPM would typically involve collecting more data or information that enables the development of better data sets of algorithms.

One of the fundamentals of reducing uncertainty is increasing sample size. Therefore, Phase 2 of the project should be designed and resourced to maximise sample size (ie number of test vehicles in a wide variety of relevant test conditions), as well as number of (repeat) measurements (vehicle emission and performance variables).

10.2.6 Vehicles

The priority vehicle classes and emission control technologies were identified in Chapter 9, and these varied pollutant to pollutant. In summary, the key priority vehicles were dominated by:

- LCV Diesel – with early to mid-Euro standard emission technology
- Car Diesel – with early to mid-Euro standard emission technology
- Car Petrol – with early to mid-Euro standard emission technology
- HDV Diesel Articulated 34–40 t.

It is recommended that emission monitoring is targeted to these vehicle types, with the specific aim of reducing uncertainty in VEPM predictions of total emissions and average fleet emission factors. The results of the assessment identified that the high-priority vehicle classes are primarily light-duty petrol and diesel vehicles, although larger articulated HDVs are near the top of the list for $PM_{2.5}$ and NO_2. It is recommended that these vehicle classes should be the focus of any future studies on vehicle emission monitoring.

Selecting specific test vehicles is challenging, due to the large number of make/model combinations for each vehicle class and emission technology type. It is therefore recommended that a more detailed fleet examination is undertaken (including vehicle sales data) to identify the top 10 vehicle makes/models in the current on-road fleet for the prioritised vehicle emission control technology classes identified in this study.

In addition to accurately quantifying the real-world emissions of relevant vehicle types and emission technologies, to fully inform Phase 2 it is important to improve our understanding of the impact of vehicle state and performance (hot-running/cold-start emissions, speed, congestion, degradation, etc).

10.3 Costs

An approximate cost for each of the recommended monitoring methods has been provided by service providers, based on a high-level scope and a general description of the services likely to be required. The costs listed below should be treated as a starting point for budget planning and subject to confirmation by service providers, once the detail of the monitoring programme has been scoped.

A PEMS study monitoring ~ 35 vehicles, including a small number of HDVs, has been costed at approximately $120,000. This costing is based on the New Zealand PEMS study (Kuschel et al., 2019) and would provide a data set very similar to that of the original PEMs study and subject to the same limitations. Each vehicle test run would provide approximately 90 minutes of data for the same variables as those provided in the previous PEMS study.

The key limitation to a PEMS study is likely to be sample size. To overcome this limitation, it is recommended that a complementary RSD programme is run. The RSD data would be used to:

- check the fleet-wide representativeness of the PEMS data
- further enhance our understanding of vehicle degradation on emissions
- add another data set to New Zealand's long-term (2002–2015) emission trend assessment.

The cost of running a complementary RSD programme on15 sites in one city (30,000 valid measurements) has been costed at approximately $100,000 to $120,000. The duration of the RSD monitoring programme would likely be approximately four weeks but ultimately, the programme duration would be determined by the weather.

If a single-site roadside or tunnel air quality monitoring study was selected to collect the data required by a project of this type, it would require instruments to measure $PM_{2.5}$, PM_{10}, NO_x and potentially other relevant pollutants such as (speciated) VOCs. For a roadside study, these instruments would be installed in environmentally secure housing. In addition to the air quality parameters, the study would need to monitor meteorological conditions and traffic counts. The cost of key items associated with a roadside or tunnel air quality monitoring study are:

- site installation and decommissioning $6,500
- monthly equipment lease $7,000
- monthly operation/service costs $1,500
- monthly data checks and quality assurance $1,000
- electricity connection and disconnection $2,000
- monthly electricity supply $500
- monthly traffic count monitoring $800.

The total cost for a six-month single-site roadside or tunnel air quality monitoring programme would be in the order of $75,000.

If a near-road plume-measurement-monitoring study was selected to collect the data required by a project of this type, it would likely require at least two complete ambient air quality monitoring sites, as detailed above. A monitoring programme of this nature that was run for six months would cost in the order of $150,000.

In New Zealand at this point, mobile on-road plume measurements are used only for research and there are no local service providers; therefore, it was not possible to obtain a cost estimate for a monitoring programme of this type.

10.4 Recommendations for real-world testing of vehicle emissions and fuel use

All the monitoring methods reviewed in this study can provide large and robust emission data that would assist in achieving the Phase 2 objectives, including the development, maintenance and validation of the VEPM. However, given resource constraints, designing and running an all-encompassing programme for emission and fuel use monitoring is not practical.

Considering the Phase 2 project requirements and the pros and cons of the available monitoring methods, it is recommended that the Phase 2 monitoring programme should consist of a three-pronged approach: that is, using PEMS, RSD and tunnel studies.

In particular, PEMS monitoring meets the following Phase 2 project criteria:

- research objective
- pollutants
- spatial/temporal scale
- real-world emissions
- emission types.

Is it important to note that at least three providers in New Zealand are capable of running a PEMS programme. The National Institute of Water and Atmospheric Research (NIWA) has the equipment (although it will need servicing) and expertise to run an RSD monitoring programme. Tunnel studies are an excellent way to gain high-level insights in prediction errors and potential bias issues.

One limitation of RSD monitoring must be noted and considered before settling on a plan to undertake the Phase 2 monitoring programme. The two RSD monitors that are in Australia and New Zealand only measure NO – measurement of NO_2 is not possible. The possible solutions to this limitation could be to require leasing an upgraded version of the RSD monitor that is capable of measuring NO_2; to be comfortable with relying on assumptions around NO_x/NO_2 ratios derived from the literature; or using, for instance, Monte Carlo error propagation to quantify the uncertainty in NO_x measurements (Smit et al., 2021).

In summary, notwithstanding the limitation noted above, the recommended Phase 2 monitoring programme is practical, as it can be achieved using local expertise and equipment.

11 Summary of key findings and conclusion

The objective of this project, as defined by Waka Kotahi, was to provide a method that would allow development and improvement in the measurement of New Zealand-specific light- and heavy-vehicle emission factors. To achieve this objective, five key project tasks were undertaken, as outlined earlier in Section 1.2. The results of each of these tasks are summarised in the following sections.

11.1 Task A

Task A was to collate and analyse real-world measurement data, including international studies.

One of the deliverables defined in the project scope was to provide an up-to-date database of New Zealand and international real-world heavy- and light-vehicle emission factors that would be representative of the New Zealand fleet emissions. The aim was for the database to be used, after the completion of this study, to help fill identified knowledge gaps in the VEPM with available real-world data before proceeding to conducting expensive emission testing. While the papers that summarised the results and conclusions from the international real-world emission studies were easily accessible, it was likely that getting access to the actual emission data sets from the authors of the relevant studies would be a time-consuming and resource-intensive task, and not always successful. Therefore, the immediate objectives of this project were achieved by using the summary results described in the relevant papers but given the resource constraints of this project, it was not possible to collect the international real-world emission measurements and collate them in a database.

The main input variables that were consistently reported as being most relevant and/or uncertain were VKT and fleet mix (population, annual mileage, share urban/rural/freeway), (hot-running) emission factors, average trip length (number of cold starts), average speed (driving conditions) and road gradient (see Chapter 3). The search of the international literature identified that PEMS data would be the data source most likely to meet the needs of this project. The international PEMS data set was supplemented by data collected in a New Zealand-run PEMS programme. A high-level comparison of the international PEMS data and the VEPM emission factors indicated that the VEPM was potentially underestimating the real-world emissions of PM, NO_x and CO_2 by factors of between 1.6 and 2.5 (see Section 7.6). While a comparison with VFEM fuel factors was not undertaken, this underestimation may also be relevant to the accuracy of the VFEM GHG emission predictions.

11.2 Task B

Task B was to develop a method of effectively estimating the emissions of light- and heavy-duty vehicles in the New Zealand fleet, including consideration of New Zealand-specific fleet vehicle types, driving speeds and route characteristics and their impacts on real-world fuel consumption and emissions.

The pollutants $PM_{2.5}$, PM_{10}, NO_x and CO_2 were identified as causing the key health and GHG impacts from vehicles operated in New Zealand (see Chapter 2). A national vehicle emissions inventory approach, using VEPM emission factors and New Zealand-specific vehicle activity and roadway data, was used to effectively estimate the emissions of light- and heavy-duty vehicles in the New Zealand fleet (see Chapters 4 and 6).

11.3 Task C

Task C was to use the above method to identify and prioritise knowledge gaps in our understanding of real-world vehicle fuel use and pollutant emissions.

The UET was developed to ingest the output from the national emissions inventory and uncertainty/sensitivity analysis and then to objectively and quantitatively identify and prioritise knowledge gaps in our understanding of real-world vehicle fuel use and pollutant emissions (see Chapter 5).

11.4 Task D

Task D was to make recommendations regarding the vehicle types that should be prioritised for real-world emissions measurement, to address the identified gaps in knowledge.

For each pollutant considered, detailed recommendations for priority vehicle types and emission control technologies have been made. Light-duty petrol and diesel vehicles dominated the vehicle classes that had the highest impact on fleet emissions as well as the highest level of uncertainty. However, heavy-duty articulated trucks featured as having high impact and high uncertainty for both $PM_{2.5}$ and NO_2 (see Chapter 9).

Before this study, previous research (Kuschel et al., 2019) had indicated that HDV emissions were likely to be a key knowledge gap, principally because there was a very limited amount of HDV emission test data available. The analysis presented in this report objectively shows that on a national inventory scale, HDVs are less important than was initially expected, when considering both uncertainty in emissions factors and the relative contribution of HDVs to total emissions. The VEPM approach for defining the vehicle classes was used for this study; that is, HDVs were disaggregated into numerous subclasses. It is likely that HDVs would have been higher in the ranking of priority emission measurement targets in this study if:

1. all HDVs had been grouped into one class and the analysis re-run

and/or

2. the emission inventory and UET had been run on an urban-area scale where speeds are lower and the percentage of HDVs is likely to be higher, rather than on a national scale.

11.5 Task E

Task E was to recommend a monitoring method that would fill the knowledge gaps identified.

A review of the available methods for measuring vehicle emissions was undertaken. A set of criteria was developed for identifying a method that would provide a cost-effective programme for vehicle emissions monitoring to fill the high-priority and relevant data gaps. A three-pronged monitoring approach has been recommended, with a primarily PEMS programme being undertaken followed by a complementary RSD monitoring programme and tunnel study (see Chapter 10).

11.6 Conclusion

Having completed these five tasks, we conclude that the project's objective to provide a method that will allow development and improvement in the measurement of New Zealand-specific light- and heavy-vehicle emissions factors has been achieved.

It is interesting to note that the recent real-world vehicle emission study undertaken in New Zealand (Kuschel et al., 2019) recommended the investigation of real-world $PM_{2.5}$ emissions from HDVs, as well as the impacts of vehicle type, load, speed and route characteristics on HDV emissions. However, the outcomes of this study suggest that greater benefit will be gained by putting the primary focus of any future emission-monitoring studies on collecting more LDV emission data, with a secondary focus on HDV emissions specifically from the perspective of reducing the uncertainty in the VEPM predictions. Nevertheless, new emissions data for New Zealand vehicles are always valuable and useful for updating the VEPM emission factors, as well as reducing potential bias (systematic errors) in VEPM emission factors.

12 Recommendations for further work

12.1 Follow-up investigations from this study

During this study, several data gaps and issues were identified by the reviewers, Project Steering Group and research team. These are listed below and we recommend they should be considered for future investigation:

- The current project did not provide improved vehicle emission factors that could be incorporated directly into the VEPM. Potentially, improved emission factors could be generated as a follow-up investigation to this study, subject to confirming the representativeness of the international data for New Zealand fleet emissions (see the next bullet point) and subject to gaining access to the relevant international data (see Section 11.1).
- The representativeness of the international data for New Zealand fleet emissions should be explored to prove or disprove the value of the investment required to collect the data for each of the sources and to collate a database. Issues such as sulphur content and quality of fuel are likely to be key points of difference between the New Zealand and international emissions measurements. The TER diesel emissions database used in this study was normalised to a common sulphur content, basically converting the PM emission results of old test programmes to reflect current fuel quality standards (< 10 ppm S). If the international data is shown to be representative or it can be converted to a New Zealand equivalent, then this study has identified the relevant data sets to provide a focused target for sourcing the data and allowing that database to fill the identified knowledge gaps in the VEPM and VFEM, rather than going straight to expensive emission testing.
- End-use expectations for the UET should be revisited and confirmed. In this study, the UET was used to provide a macro-view of the national fleet (the scale was New Zealand). However, the method and tools developed for this study could well be applied on a more disaggregated scale (eg main road types) and on different fleet profiles (including a greater proportion of HDVs). A study that considers these factors may provide further explanation of why HDVs did not feature strongly in the target vehicles.
- Using CO_2 emission factors as a baseline (or marker) for uncertainty estimation should be considered because they are relatively 'well behaved'. Uncertainty estimates for NO_x and PM emission factors should be based on their relationship with CO_2 emissions and/or fuel use.
- The New Zealand PEMS and RSD database should be integrated (using CO_2 emission factors as a baseline) to deliver a complementary and wider data source for the purpose of informing the recommendations for future investigations presented in this study (and others).
- The investigations explored in this project should be expanded to include other GHGs (eg N_2O, HFCs and CH_4).
- The impact of brake and tyre wear on $PM_{2.5}$ emission factors and fleet emissions should be considered further and quantified.
- The current vehicle emission models (the VEPM and VFEM) should be upgraded to enable them to easily quantify the future impact of changes to, or implementation of, management policies for vehicle emissions or vehicle fleets. While the current key policy direction identified by the Project Steering Group is GHGs, achieving New Zealand's carbon emission target is a very important driver, which means real-world CO_2 and other GHG emission predictions should be a focus.
- Consideration of the direction of vehicle emissions intervention policy should be integrated into the process of identifying target vehicle classes for emission monitoring. For example, it is expected that there will be a big uptake of electric vehicles for the LDV fleet; therefore, passenger cars could be moved

down the priority emission measurement list in the future. Due to current governmental priorities and the available technology, an intervention policy for the HDV fleet will come later than for the LDV fleet. Therefore, more information about the HDV fleet is expected to inform policy in the near future, and this could be considered in the process of identifying target vehicle classes for emission monitoring.

- The focus on PEMS and RSD data for future monitoring activities will be successful in informing initial efforts to benchmark fleet emissions. However, other monitoring methods such as tunnel studies will likely be required as efforts move from the characterisation of fleet emissions to the management and control of emissions. For example, tampering has been identified as a source of higher emissions in Europe in large commercial fleets. Efforts to target these vehicles will most likely require spot inspection and/or other monitoring strategies.

12.2 New emission-monitoring methods for New Zealand

The review of methods of vehicle emission monitoring has raised the profile of some emerging technologies. While we believe these new methods are not as well suited to the needs of Phase 2 as those that have been identified in this study, these new methods should be investigated and considered for future studies. The potential use of on-board diagnostic data is a case in point.

12.3 VEPM update recommendations

Extensive use was made of the VEPM during this study. The UET served the project very well and the recent update of it proved to be a valuable development. Several data gaps and possible improvements were noted in this study. By pollutant, these were:

- NO_x and NO_2:
  - gradient correction factors/information/sources for:
    - petrol LCVs
    - rigid HDVs
    - articulated HDVs
    - buses
  - cold-start emission factors for:
    - rigid HDVs
    - articulated HDVs
    - buses
- CO_2:
  - fuel correction factor and degradation:
    - defaulted to 1 (no adjustment) for all vehicle classes/categories
  - cold-start emission factors for:
    - all hybrid vehicles
    - rigid HDVs
    - articulated HDVs
    - buses
- PM exhaust:
  - cold-start emission factors for:
    - petrol passenger cars

    - petrol LCVs
    - rigid HDVs
    - articulated HDVs
    - buses
- PM non-exhaust:
  - brake and tyre wear factors/sources that can distinguish changes in technology and the difference between weights for internal combustion engine vehicles and electric vehicles.

The following general data gaps were also identified in the VEPM:

- Assumed fuel specification does not match actual New Zealand fuel quality monitoring.
- The impact of tampering with emission reduction systems cannot be estimated, specifically with exhaust gas recirculation and selective catalytic reduction systems on heavy vehicles.

12.4 Information gaps and emerging issues

During this investigation, the following information gaps and emerging issues were identified and we recommend these are considered for future investigations:

- better understanding of the effects of changing the vehicle fleet emission profile on the long-term trends in roadside ambient air quality
- non-exhaust emissions – evaporative emissions and re-suspended road dust
- emerging issues such as tampering by vehicle owners (eg DPF removal, Selective Catalytic Reduction [SCR emulation]) and the impact of re-suspended road dust from electric vehicles
- the black carbon fraction of particulate emissions, as a climate forcer or GHG – it is now widely recognised that black carbon is a short-lived climate pollutant and although it is not routinely inventoried, it is important for the dual consideration of conventional and climate pollutant impacts for which prominent PM sources, including vehicles, are responsible.

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Appendix A: UET and OAT analysis for NO_x – vehicle classes

Appendix A is available as a downloadable PDF file on the Waka Kotahi website:
www.nzta.govt.nz/resources/research/reports/687

Appendix B: UET analysis for NO_x – emission technology

Appendix B is available as a downloadable PDF file on the Waka Kotahi website:
www.nzta.govt.nz/resources/research/reports/687

Appendix C: Comparison of PEMS and VEPM emission factors

Vehicle class	Country	Traffic situation (road gradient)	Mean NO_x EF (g/km)	Uncertainty (%)	Reference	VEPM NO_x EF (g/km)
PC-P E_1	EU	urban (unknown)	0.24	77	De Vlieger (1997)	0.49
PC-P E_1	EU	rural (unknown)	0.17	81	De Vlieger (1997)	0.49
PC-P E_1	EU	freeway (unknown)	0.14	75	De Vlieger (1997)	0.72
PC-P E_0	UK	urban (none)	1.20	70	Daham et al. (2010)	1.94
PC-P E_1	UK	urban (none)	0.89	36	Daham et al. (2010)	0.82
PC-P E_2	UK	urban (none)	0.53	70	Daham et al. (2010)	0.35
PC-P E_3	UK	urban (none)	0.47	122	Daham et al. (2010)	0.08
PC-P E_4	UK	urban (none)	0.65	42	Daham et al. (2010)	0.04
HDV-D E_III	US	urban (none)	2.80	10	Gierczak et al. (2007)	2.94
LCV-D E_3	UK	urban-rural (unknown)	1.86	76	Hadavi et al. (2012)	1.43
PC-D US_Tier 2	US	urban (variable)	0.57	112	Thompson et al. (2014)	0.97
PC-D US_Tier 2	US	highway (variable)	0.48	358	Thompson et al. (2014)	0.99
PC-D US_Tier 2	US	hilly (variable)	0.86	165	Thompson et al. (2014)	2.36
PC-D E_6	UK	urban (flat)	0.43	32	O'Driscoll et al. (2016)	0.45
PC-D E_6	UK	motorway (flat)	0.31	39	O'Driscoll et al. (2016)	0.42
HDV-D E_VI	EU	low speed (variable)	2.91	89	Grigoratos et al. (2019)	0.14
HDV-D E_VI	EU	medium speed (variable)	0.49	96	Grigoratos et al. (2019)	0.06
HDV-D E_VI	EU	high speed (variable)	0.24	128	Grigoratos et al. (2019)	0.05
HDV-D E_1_used	NZ	low speed – urban (variable)	5.28	34	Kuschel et al. (2019)	3.66
HDV-D E_1_used	NZ	medium speed – motorway (variable)	3.28	37	Kuschel et al. (2019)	3.85
HDV-D E_1_used	NZ	medium speed – rural (variable)	2.77	102	Kuschel et al. (2019)	3.85
HDV-D E_2_new	NZ	low speed – urban (variable)	2.79	17	Kuschel et al. (2019)	3.91

Vehicle class	Country	Traffic situation (road gradient)	Mean NO_x EF (g/km)	Uncertainty (%)	Reference	VEPM NO_x EF (g/km)
HDV-D E_2_new	NZ	high speed – motorway (variable)	1.38	21	Kuschel et al. (2019)	4.18
HDV-D E_2_new	NZ	medium speed – rural (variable)	1.18	65	Kuschel et al. (2019)	4.00
HDV-D E_V_new	NZ	low speed – urban (variable)	5.20	64	Kuschel et al. (2019)	1.50
HDV-D E_V_new	NZ	high speed – motorway (variable)	3.67	19	Kuschel et al. (2019)	0.72
HDV-D E_V_new	NZ	medium speed – rural (variable)	4.55	22	Kuschel et al. (2019)	0.62
SUV-D E_1_used	NZ	low speed – urban (variable)	5.13	331	Kuschel et al. (2019)	0.93
SUV-D E_1_used	NZ	high speed – motorway (variable)	4.66	91	Kuschel et al. (2019)	1.09
SUV-D E_1_used	NZ	medium speed – rural (variable)	2.54	594	Kuschel et al. (2019)	0.94
SUV-D E_4_new	NZ	low speed – urban (variable)	2.50	21	Kuschel et al. (2019)	0.77
SUV-D E_4_new	NZ	high speed – motorway (variable)	1.41	13	Kuschel et al. (2019)	0.94
SUV-D E_4_new	NZ	medium speed – rural (variable)	0.68	88	Kuschel et al. (2019)	0.71
SUV-P E_3_new	NZ	low speed – urban (variable)	0.21	312	Kuschel et al. (2019)	0.27
SUV-P E_3_new	NZ	medium speed – rural (variable)	0.18	193	Kuschel et al. (2019)	0.29
LCV-D E_4_new	NZ	low speed – urban (variable)	2.06	98	Kuschel et al. (2019)	1.15
LCV-D E_4_new	NZ	medium speed – motorway (variable)	1.20	28	Kuschel et al. (2019)	1.11
LCV-D E_4_new	NZ	medium speed – rural (variable)	0.81	107	Kuschel et al. (2019)	1.11
LCV-D E_5_new	NZ	low speed – urban (variable)	1.28	200	Kuschel et al. (2019)	1.26
LCV-D E_5_new	NZ	high speed – motorway (variable)	0.84	21	Kuschel et al. (2019)	1.92
LCV-D E_5_new	NZ	medium speed – rural (variable)	0.88	508	Kuschel et al. (2019)	1.34

Vehicle class	Country	Traffic situation (road gradient)	Mean CO_2 EF (g/km)	Uncertainty (%)	Reference	VEPM CO_2 EF (g/km)
PC-P E_0	UK	urban (none)	369	23%	Daham et al. (2010)	177
PC-P E_1	UK	urban (none)	444	15%	Daham et al. (2010)	179
PC-P E_2	UK	urban (none)	511	18%	Daham et al. (2010)	179

Vehicle class	Country	Traffic situation (road gradient)	Mean CO_2 EF (g/km)	Uncertainty (%)	Reference	VEPM CO_2 EF (g/km)
PC-P E_3	UK	urban (none)	546	19%	Daham et al. (2010)	177
PC-P E_4	UK	urban (none)	409	19%	Daham et al. (2010)	195
LCV-D E_3	UK	urban-rural (unknown)	174	8%	Hadavi et al. (2012)	212
PC-D US_Tier 2	US	urban (variable)	255	37%	Thompson et al. (2014)	207
PC-D US_Tier 2	US	highway (variable)	144	16%	Thompson et al. (2014)	207
PC-D US_Tier 2	US	hilly (variable)	204	84	Thompson et al. (2014)	207
HDV-D E_VI	EU	low speed (variable)	2284	32	Grigoratos et al. (2019)	333
HDV-D E_VI	EU	medium speed (variable)	1103	71	Grigoratos et al. (2019)	340
HDV-D E_VI	EU	high speed (variable)	645	17	Grigoratos et al. (2019)	380
HDV-D E_1_used	NZ	low speed – urban (variable)	548	80	Kuschel et al. (2019)	339
HDV-D E_1_used	NZ	medium speed – motorway (variable)	350	268	Kuschel et al. (2019)	349
HDV-D E_1_used	NZ	medium speed – rural (variable)	258	88	Kuschel et al. (2019)	349
HDV-D E_2_new	NZ	low speed – urban (variable)	366	33	Kuschel et al. (2019)	327
HDV-D E_2_new	NZ	high speed – motorway (variable)	232	14	Kuschel et al. (2019)	357
HDV-D E_2_new	NZ	medium speed – rural (variable)	210	6	Kuschel et al. (2019)	340
HDV-D E_V_new	NZ	low speed – urban (variable)	435	10	Kuschel et al. (2019)	324
HDV-D E_V_new	NZ	high speed – motorway (variable)	203	19	Kuschel et al. (2019)	374
HDV-D E_V_new	NZ	medium speed – rural (variable)	180	36	Kuschel et al. (2019)	334
SUV-D E_1_used	NZ	low speed – urban (variable)	317	22	Kuschel et al. (2019)	222
SUV-D E_1_used	NZ	high speed – motorway (variable)	295	98	Kuschel et al. (2019)	234
SUV-D E_1_used	NZ	medium speed – rural (variable)	192	152	Kuschel et al. (2019)	213
SUV-D E_4_new	NZ	low speed – urban (variable)	497	8	Kuschel et al. (2019)	222
SUV-D E_4_new	NZ	high speed – motorway (variable)	242	27	Kuschel et al. (2019)	234
SUV-D E_4_new	NZ	medium speed – rural (variable)	233	11	Kuschel et al. (2019)	213

Vehicle class	Country	Traffic situation (road gradient)	Mean CO_2 EF (g/km)	Uncertainty (%)	Reference	VEPM CO_2 EF (g/km)
SUV-P E_3_new	NZ	low speed – urban (variable)	382	257	Kuschel et al. (2019)	209
SUV-P E_3_new	NZ	medium speed – rural (variable)	195	168	Kuschel et al. (2019)	185
LCV-D E_4_new	NZ	low speed – urban (variable)	373	29	Kuschel et al. (2019)	212
LCV-D E_4_new	NZ	medium speed – motorway (variable)	236	286	Kuschel et al. (2019)	210
LCV-D E_4_new	NZ	medium speed – rural (variable)	228	96	Kuschel et al. (2019)	210
LCV-D E_5_new	NZ	low speed – urban (variable)	387	101	Kuschel et al. (2019)	222
LCV-D E_5_new	NZ	high speed – motorway (variable)	283	52	Kuschel et al. (2019)	246
LCV-D E_5_new	NZ	medium speed – rural (variable)	220	18	Kuschel et al. (2019)	221

Vehicle class	Country	Traffic situation (road gradient)	Mean $PM_{2.5}$ EF (g/km)	Uncertainty (%)	Reference	VEPM $PM_{2.5}$ EF (g/km)
PC-D US_Tier 2	US	urban (variable)	0.227	250	Thompson et al. (2014)	0.096
PC-D US_Tier 2	US	highway (variable)	0.023	199	Thompson et al. (2014)	0.102
PC-D US_Tier 2	US	hilly (variable)	1.190	220	Thompson et al. (2014)	0.251
HDV-D E_1_used	NZ	low speed – urban (variable)	0.727	152	Kuschel et al. (2019)	0.143
HDV-D E_1_used	NZ	medium speed – motorway (variable)	0.702	219	Kuschel et al. (2019)	0.122
HDV-D E_1_used	NZ	medium speed – rural (variable)	0.143	97	Kuschel et al. (2019)	0.122
HDV-D E_2_new	NZ	low speed – urban (variable)	0.354	42	Kuschel et al. (2019)	0.152
HDV-D E_2_new	NZ	high speed – motorway (variable)	0.267	43	Kuschel et al. (2019)	0.186
HDV-D E_2_new	NZ	medium speed – rural (variable)	0.177	73	Kuschel et al. (2019)	0.168
HDV-D E_V_new	NZ	low speed – urban (variable)	0.046	177	Kuschel et al. (2019)	0.046
HDV-D E_V_new	NZ	high speed – motorway (variable)	0.015	237	Kuschel et al. (2019)	0.039
HDV-D E_V_new	NZ	medium speed – rural (variable)	0.018	160	Kuschel et al. (2019)	0.041
SUV-D E_1_used	NZ	low speed – urban (variable)	0.210	198	Kuschel et al. (2019)	0.123
SUV-D E_1_used	NZ	high speed – motorway (variable)	0.151	43	Kuschel et al. (2019)	0.243

Vehicle class	Country	Traffic situation (road gradient)	Mean $PM_{2.5}$ EF (g/km)	Uncertainty (%)	Reference	VEPM $PM_{2.5}$ EF (g/km)
SUV-D E_1_used	NZ	medium speed – rural (variable)	0.101	55	Kuschel et al. (2019)	0.151
SUV-D E_4_new	NZ	low speed – urban (variable)	0.079	35	Kuschel et al. (2019)	0.061
SUV-D E_4_new	NZ	high speed – motorway (variable)	0.038	170	Kuschel et al. (2019)	0.059
SUV-D E_4_new	NZ	medium speed – rural (variable)	0.027	93	Kuschel et al. (2019)	0.055
SUV-P E_3_new	NZ	low speed – urban (variable)	0.002	122	Kuschel et al. (2019)	0.002
SUV-P E_3_new	NZ	medium speed – rural (variable)	0.002	496	Kuschel et al. (2019)	0.001
LCV-D E_4_new	NZ	low speed – urban (variable)	0.063	103	Kuschel et al. (2019)	0.049
LCV-D E_4_new	NZ	medium speed – motorway (variable)	0.029	331	Kuschel et al. (2019)	0.064
LCV-D E_4_new	NZ	medium speed – rural (variable)	0.045	101	Kuschel et al. (2019)	0.064
LCV-D E_5_new	NZ	low speed – urban (variable)	0.004	118	Kuschel et al. (2019)	0.001
LCV-D E_5_new	NZ	high speed – motorway (variable)	0.003	133	Kuschel et al. (2019)	0.001
LCV-D E_5_new	NZ	medium speed – rural (variable)	0.003	199	Kuschel et al. (2019)	0.001