THE REAL URBAN EMISSIONS INITIATIVE

Development and application of a United States real-world vehicle emissions database

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OCTOBER 2020

ACKNOWLEDGMENTS

The authors would like to thank the Colorado Department of Public Health and Environment and Virginia Department of Environmental Quality for sharing data collected in their vehicle remote sensing programs. The authors also thank the University of Denver for making their remote sensing data publicly available.

FIA Foundation and the International Council on Clean Transportation (ICCT) have established The Real Urban Emissions (TRUE) Initiative. The TRUE initiative seeks to supply cities with data regarding the real-world emissions of their vehicle fleets and equip them with technical information that can be used for strategic decision making. TRUE will use a combination of measurement techniques to produce a granular picture of the on-road emissions of the entire vehicle fleet by make, model, and model year.

INTRODUCTION

Emissions from motor vehicles and their fuels contribute to ambient levels of ozone, fine particulate matter, nitrogen dioxide (NO_2), sulfur dioxide, and carbon monoxide (CO), which are all pollutants for which the United States Environmental Protection Agency (EPA) has established health-based National Ambient Air Quality Standards (NAAQS). These pollutants are linked with adverse health impacts and premature mortality. Today, 127 million people live in areas designated nonattainment for one or more of the current NAAQS.[1]

Cars and light- and heavy-trucks are a particular problem for the more than 50 million people who live, work, or go to school in close proximity to high-traffic roadways.[2] Vehicles are a significant contributor to air pollution near roads, with gasoline light-duty vehicles alone accounting for more than 50% of near-road concentrations of some toxic and criteria pollutants.[3] Diesel trucks further contribute to pollution hotspots in urban areas.[4]

The United States has a long history of managing and reducing emissions from vehicles. California first started regulating vehicles in the 1960s, and the U.S. Clean Air Act, passed in 1970 mandates reductions in vehicle emissions. Over the years, these standards have progressively been made more stringent. New cars, sport utility vehicles (SUVs) and pickup trucks emit roughly 99% less hydrocarbons, carbon monoxide, nitrogen oxides, and particle emissions than their 1970 counterparts. New heavy-duty trucks and buses are also roughly 99% cleaner than 1970 models.[5] In addition, fuels are much cleaner—lead has been eliminated and sulfur levels are more than 90% lower than they were prior to regulation.

However, these emission reductions values are only achieved by new, properly operating vehicles over a defined test cycle. There are many ways that real-world emissions can increase, and due to the effectiveness of the emission control systems used in modern vehicles, any defect or deterioration in the system can result in a large increase in emissions. This was demonstrated by the Volkswagen diesel emissions scandal, where the use of illegal defeat devices led to real-world emissions of nitrogen oxides (NO_x) that were 5-35 times higher than those allowed on laboratory certification emissions tests.[6]

A relatively small number of defective or deteriorated systems can have a large impact on overall emissions and addressing all the causes of higher emissions is difficult. Despite improvements made to vehicle regulatory programs in the United States, there remains uncertainty about many aspects of real-world emissions from the vehicle fleet in the country, including:

- The real-world durability of all vehicles, not just those properly used and maintained.
- The emissions as vehicles deteriorate beyond the official emission useful life.
- How often malfunctions occur, how frequently repairs are made, and the emissions impact of the malfunctions.
- How much tampering occurs and the emissions impact of the tampering.
- Whether there are emission defects that are not being reported.
- Whether there are defeat devices that have not been identified.
- The impact of different speeds and accelerations on emissions.
- The impact of ambient conditions on emissions.

More real-world emissions data are needed to understand the impact of motor vehicles on local air quality and help policymakers develop effective policy solutions. Information on real-world emissions performance can also help consumers make informed

1 U.S. Environmental Protection Agency, "Summary Nonattainment Area Population Exposure Report," (April 30, 2020), https://www3.epa.gov/airquality/greenbook/popexp.html.

2 U.S. Census Bureau, "American Housing Survey for the United States: 2009," H150/09 (U.S. Government Printing Office, March 2011), https://www.census.gov/prod/2011pubs/h150-09.pdf.

3 Eric M. Fujita, David E. Campbell, Barbara Zielinska, William P. Arnott, and Judith C. Chow, "Concentrations of Air Toxics in Motor Vehicle-Dominated Environments," *Research Report (Health Effects Institute)*, no. 156 (February 2011): 3–77, https://www.healtheffects.org/publication/concentrations-air-toxics-motor-vehicle-dominated-environments.

4 Joshua S. Apte, Kyle P. Messier, Shahzad Gani, Michael Brauer, Thomas W. Kirchstetter, Melissa M. Lunden, Julian D. Marshall, Christopher J. Portier, Roel C.H. Vermeulen, and Steven P. Hamburg, High-Resolution Air Pollution Mapping with Google Street View Cars: Exploiting Big Data, *Environmental Science & Technology 51*, no. 12 (June 20, 2017): 6999–7008, https://doi.org/10.1021/acs.est.7b00891.

5 U.S. Environmental Protection Agency, "History of Reducing Air Pollution from Transportation in the United States," (September 10, 2015), https://www.epa.gov/transportation-air-pollution-and-climate-change/accomplishments-and-success-air-pollution-transportation.

6 Gregory Thompson, Daniel Carder, Arvind Thiruvengadam, and Hemanth Kappanna, "In-Use Testing of Light-Duty Diesel Vehicles in the United States" (Morgantown, WV: West Virginia University, May 2014), https://theicct.org/publications/use-emissions-testing-light-duty-diesel-vehicles-us.

purchasing decisions. The Real Urban Emissions (TRUE) Initiative was established in 2017 to supply cities with data regarding the real-world emissions of their vehicle fleets and equip them with technical information that can be used for strategic decision-making.

To date, TRUE initiative work has focused on the analysis of real-world vehicle emissions data collected in European cities using remote sensing instruments. Remote sensing is a well-established technology for non-intrusively measuring the emissions of in-use vehicles.[7] Initial work by the TRUE initiative presented methods for analyzing remote sensing data and applied these methods to investigate real-world NO_x emissions from European vehicles.[8] This work was followed by city-specific TRUE remote sensing studies in London and Paris.[9] The emissions of more than 100,000 vehicles were measured in each city, and data were analyzed to provide city officials, residents, and other stakeholders with a detailed picture of the emissions of the cities' fleets. These studies demonstrated how real-world emissions data can be used to support city-level clean air and vehicle emissions control policies and actions.

With this paper, the TRUE project turns its attention to gathering and analyzing remote sensing data in the United States using the methods and analyses learned from the previous studies in Europe. The goal of this project is to apply existing U.S. remote sensing data to further investigate how cities can use real-world data to support vehicle emissions control policies and actions. This first paper describes the data sources, data processing steps, metadata, select high-level results, and recommendations for future improvements. More detailed analyses of the database are published as separate case studies.[10]

Throughout this paper and in companion publications we will refer to the collection of remote sensing data compiled in this work as the TRUE U.S. database to distinguish it from other, similar, collections of vehicle remote sensing data.

The following sections give an overview of the construction of the TRUE U.S. database and how the data were processed; present important aspects of the consolidated single database; describe data analysis, high-level results, and four examples of how the data can be used; and present conclusions and recommendations for future data collection and analyses.

CONSTRUCTION OF THE TRUE U.S. DATABASE

The development and use of remote vehicle emissions sensing in the United States has grown in recent years. Early systems were pioneered by the University of Denver (DU) in the late 1980s, funded initially by the Colorado Office of Energy Conservation and later by the California Air Resources Board (CARB). Remote sensing campaigns have been conducted in 19 states and Washington, DC, as illustrated in Figure 1.[11] The figure shows which U.S. states use remote sensing, differentiated by program objectives. Currently, Colorado and Virginia are among the states most actively using remote sensing. Each state is using the technology to support vehicle inspection and maintenance (I/M) programs and is gathering several million remote sensing measurements per year.

7 Tim Dallmann, *Use of Remote-Sensing Technology for Vehicle Emissions Monitoring and Control,* (ICCT: Washington, D.C., 2018), https://theicct.org/publications/remote-sensing-briefing-dec2018.

8 Yoann Bernard, Uwe Tietge, John German, and Rachel Muncrief, *Determination of Real-World Emissions from Passenger Vehicles Using Remote Sensing Data,* (Washington, D.C.: TRUE Initiative, 2018), https://theicct.org/publications/real-world-emissions-using-remote-sensing-data.

9 Tim Dallmann, Yoann Bernard, Uwe Tietge, and Rachel Muncrief, *Remote Sensing of Motor Vehicle Emissions in Paris,* (ICCT: Washington, D.C., 2019), https://theicct.org/publications/on-road-emissions-paris-201909; Tim Dallmann et al., Remote Sensing of Motor Vehicle Emissions in London, (ICCT: Washington, D.C., 2018), https://theicct.org/publications/true-london-dec2018.

10 Yoann Bernard, Tim Dallmann, Uwe Tietge, Huzeifa Badshah, John German, *Emissions deterioration of United States light-duty gasoline vehicles and trucks,* (ICCT: Washington, DC, 2020), https://theicct.org/publications/true-us-database-emissions-deterioration-oct2020; Yoann Bernard, Tim Dallmann, Uwe Tietge, Huzeifa Badshah, John German, *Emissions distributions by vehicle age and policy implications,* (ICCT: Washington, DC, 2020), https://theicct.org/publications/true-us-database-emissions-distribution-oct2020; Yoann Bernard, Tim Dallmann, Uwe Tietge, Huzeifa Badshah, John German, *Remote sensing of heavy-duty vehicle emissions in the United States,* (ICCT: Washington, DC, 2020) https://theicct.org/publications/true-us-database-hdv-emissions-oct2020.

11 Yoann Bernard, John German, and Rachel Muncrief, *Worldwide Use of Remote Sensing to Measure Motor Vehicle Emissions,* (ICCT: Washington, D.C. 2019), https://theicct.org/publications/worldwide-use-remote-sensing-measure-motor-vehicle-emissions.

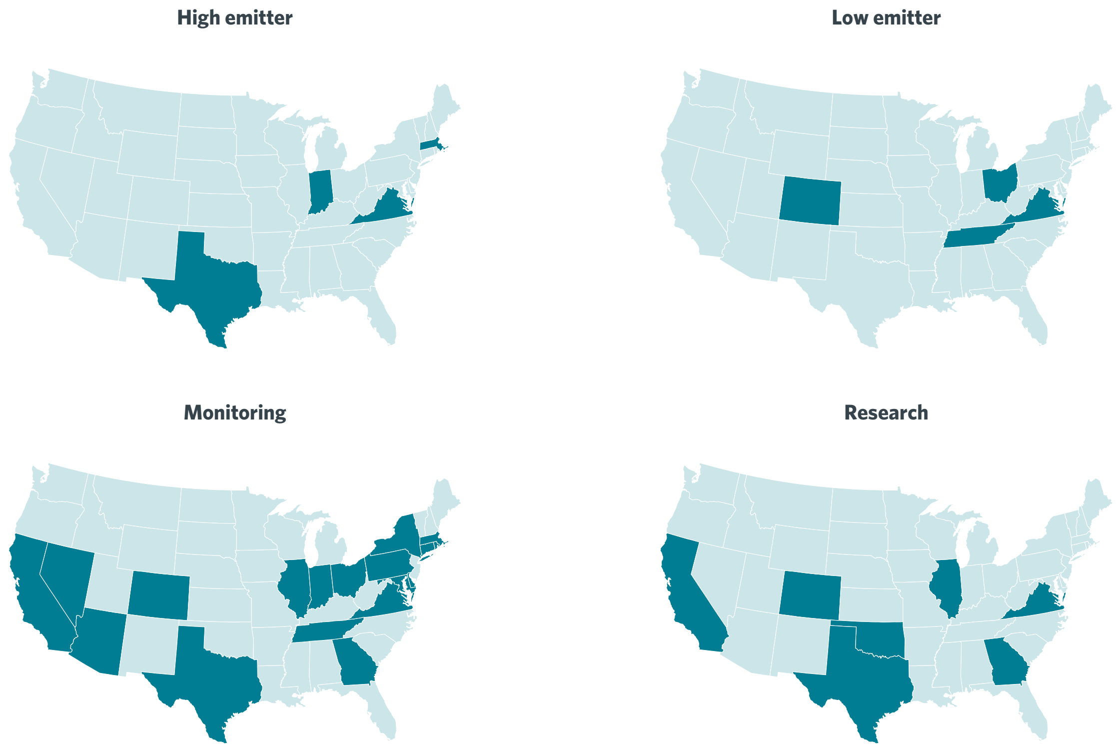


Figure 1. Map of U.S. states using remote sensing, by program use.

DATA SOURCES

Data collected by Colorado, Virginia, and the University of Denver and shared with the ICCT were used to construct the TRUE U.S. database. These data sources include approximately 60 million records and cover an impressive range of geography, ambient conditions, and driving conditions. The counties and cities for which measurements were obtained from each of the three sources are illustrated in Figure 2.

The Colorado Department of Public Health & Environment (CDPHE) uses remote sensing for their clean screen program, which was launched in October 2003 and is part of I/M programs targeting vehicles registered in the Denver Metropolitan area and North Front Range.[12] Under the clean screen program, vehicles that pass roadside remote sensing emission tests are exempt from garage-based inspection requirements. The program now collects several million records each year.

CDPHE shared data from their remote sensing program with the ICCT collected from 2010 through the first half of 2018, consisting of over 53 million emission test records. From July 2008 through 2015, CDPHE used Opus 4000 series instruments (RSD 4600) to measure emissions and transitioned to Opus 5000-series instruments from 2015 onward. The data shared with ICCT cover the pollutants nitrogen monoxide (NO), CO, carbon dioxide (CO_2), hydrocarbons (HC), and opacity.

The Virginia Department of Environmental Quality (DEQ) also uses remote sensing for their clean screen program in Northern Virginia, which they call RAPIDPASS. In 2012, the Virginia legislature approved an expansion of the on-road emission (remote sensing) program to allow up to 30% of vehicles to complete their test requirement via RAPIDPASS.[13] The DEQ also runs a high-emitter identification program using remote sensing data.[14] DEQ shared data for years 2015 through 2018 with the ICCT, consisting of approximately 5 million records collected through the use of Opus 5000 series instruments.

12 Colorado Department of Public Health & Environment, "Automobile Emissions Inspection," (May 14, 2014), https://www.colorado.gov/pacific/cdphe/automobile-emissions-inspection.

13 Virginia Department of Environmental Quality, "RAPIDPASS Virginia," (accessed May 20, 2020), https://www.deq.virginia.gov/Programs/AirCheckVirginia/ForMotoristsVehicleOwners/RAPIDPASSVirginia.aspx.

14 Virginia Department of Environmental Quality, "On-Road Emissions Program FAQ," (accessed May 20, 2020), https://www.deq.virginia.gov/Programs/AirCheckVirginia/ForMotoristsVehicleOwners/OnRoadEmissionsProgramFAQ.aspx.

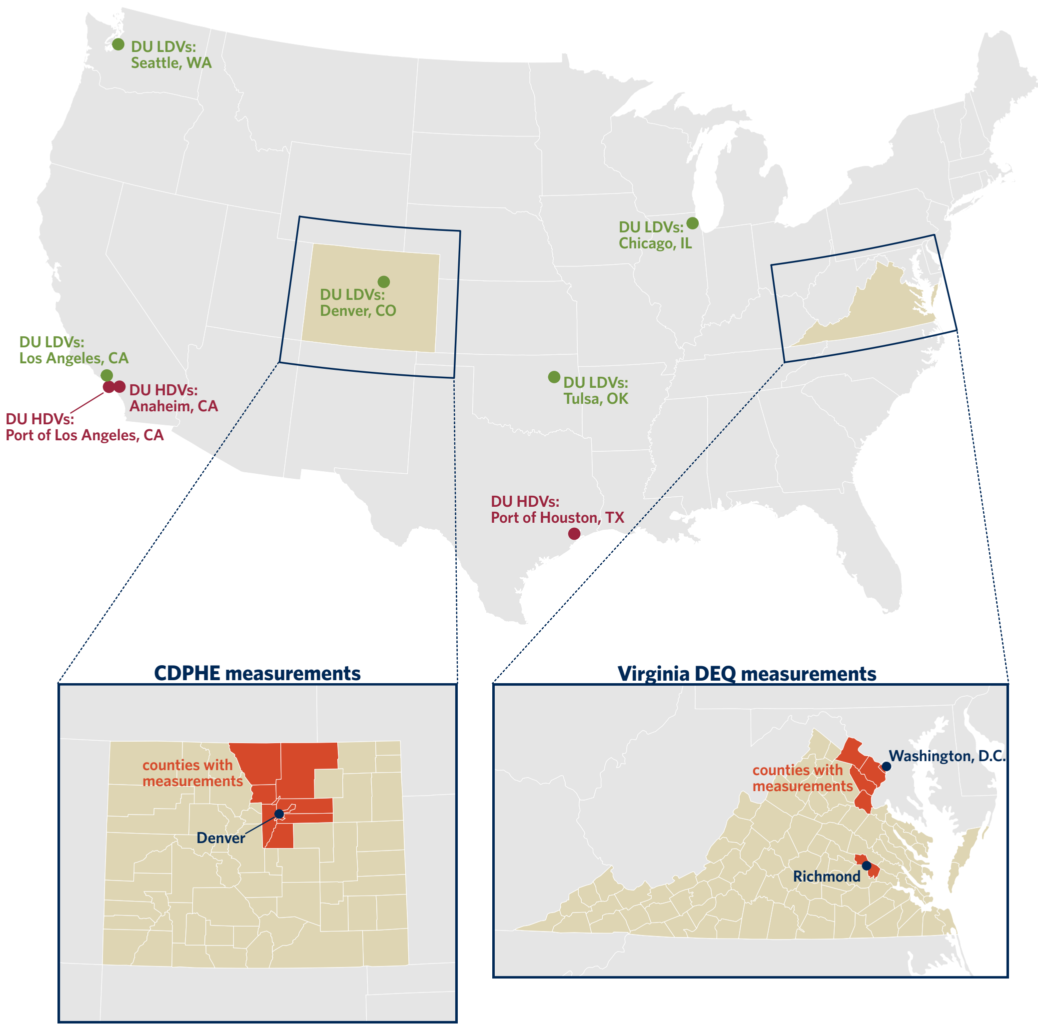


Figure 2. Measurement locations for data compiled in TRUE U.S. database.

While the OPUS 5000-series instrument used by Virginia and Colorado after 2015 is capable of measuring NO_2 emissions, none of the data reported to us included NO_2 measurements. For vehicles equipped with gasoline engines, NO_2 is expected to account for under 10% of total NO_x emissions. The NO_2 fraction can be higher in diesel exhaust, particularly for modern engines employing catalytic control technologies.[15] In this report, we focus on reporting NO emission results, as this is the NO_x species directly measured in the Colorado and Virginia programs. In companion publications we explore methods for estimating total NO_x emissions when NO_2 is not available, building on prior work in this area.[16]

The University of Denver was an early pioneer in remote sensing activities. The first open path cross-road arc lamp systems were pioneered by Gary Bishop and Donald Stedman, and they have conducted testing throughout the United States since the late 1980s. The remote sensing system developed by DU and used for LDV measurements is called the Fuel Efficiency Automotive Test (FEAT). An alternative instrument set-up is used for targeted testing of HDVs, with a light source and detector elevated to the level of HDV raised stack exhaust pipes. Remote sensing data generated by DU is shared publicly by the University of Denver

15 Chelsea V. Preble, Robert A. Harley, and Thomas W. Kirchstetter, Control Technology-Driven Changes to In-Use Heavy-Duty Diesel Truck Emissions of Nitrogeneous Species and Related Environmental Impacts, *Environ. Sci. Technol.* 53 (November 5, 2019): 14568–14576, https://doi.org/10.1021/acs.est.9b04763.

16 Bernard et al., *Determination of Real-World Emissions from Passenger Vehicles Using Remote Sensing Data.*

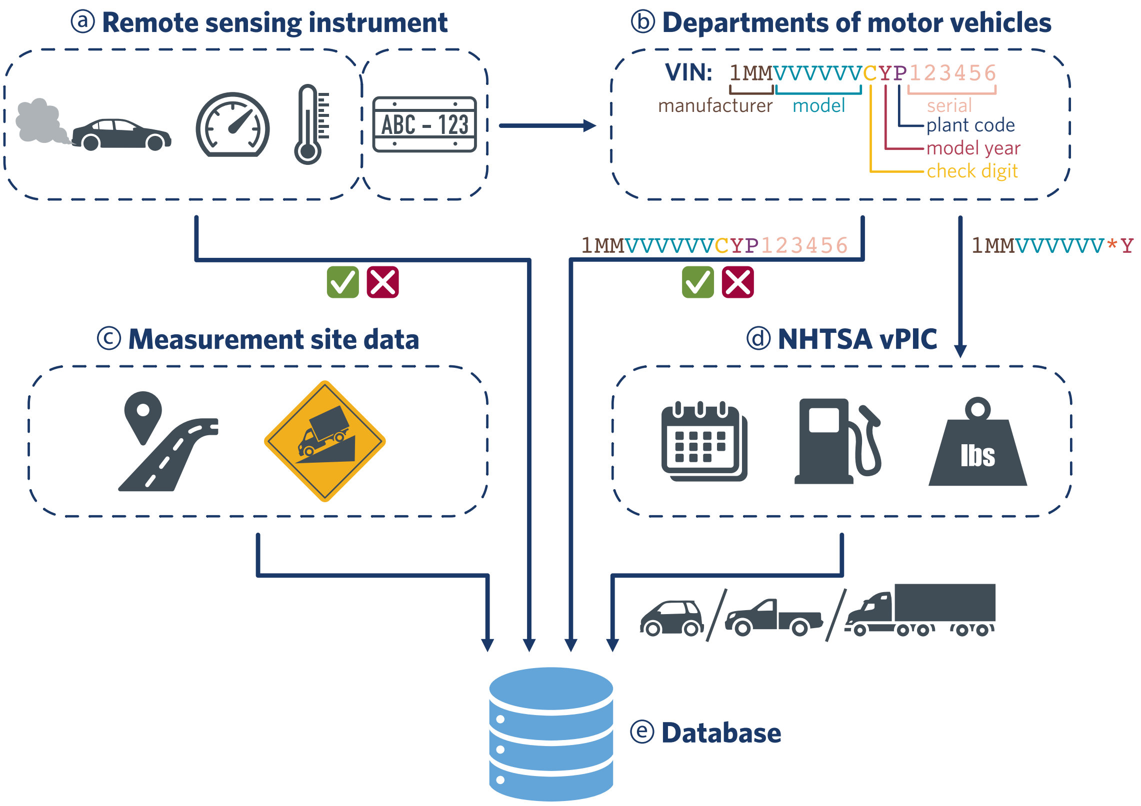


Figure 3. Schematic diagram of data sources and data processing related to the database.

Fuel Efficiency Automobile Test Data Center.[17] For LDVs, this report considers data collected from 2010 and onwards, consisting of approximately 300,000 measurements. For HDVs, data collected from 2008 and onward is considered, comprised of roughly 23,000 measurements.

DATA PROCESSING

Remote emissions measurements need to be combined with other data sources in order to support in-depth analyses. Figure 3 illustrates the process of combining different data sources in the TRUE U.S. database.

Remote sensing instruments record the concentration measurements of each emissions species relative to CO_2 above the concentration in the ambient air, the vehicle's speed and acceleration, weather conditions such as ambient temperature, and a photo of the vehicle license plate (see part A of Figure 3). Data on the measurement site, such as geographic coordinates and road slope, are recorded by instrument operators (see part C of Figure 3).

After remote sensing operators transcribe the license plate numbers from photos, the license plate numbers are transferred to the government department in charge of maintaining vehicle registration information in the state of the measurement campaign. The department determines the individual vehicle attributes, including the vehicle identification number (VIN) from the vehicle registry (see part B of Figure 3). The VIN consists of 17 characters and encodes the manufacturer, vehicle description, model year, assembly plant, and a serial number uniquely identifying individual vehicles. The VIN also includes a check digit, against which the checksum of the VIN can be compared.

Data for parts A, B, and C of Figure 3 were provided by the CDPHE, Virginia DEQ, and the University of Denver and were stored in the TRUE U.S. database. Because the quality of vehicle attributes available from registration information varies by state, we retrieved vehicle attributes for all measurement campaigns from the National Highway Traffic Safety Administration's Product Information Catalog and Vehicle Listing

17 University of Denver, Fuel Efficiency Automobile Test Data Center, "Welcome to the Fuel Efficiency Automobile Test Data Center," (December 3, 2019), http://www.feat.biochem.du.edu/.

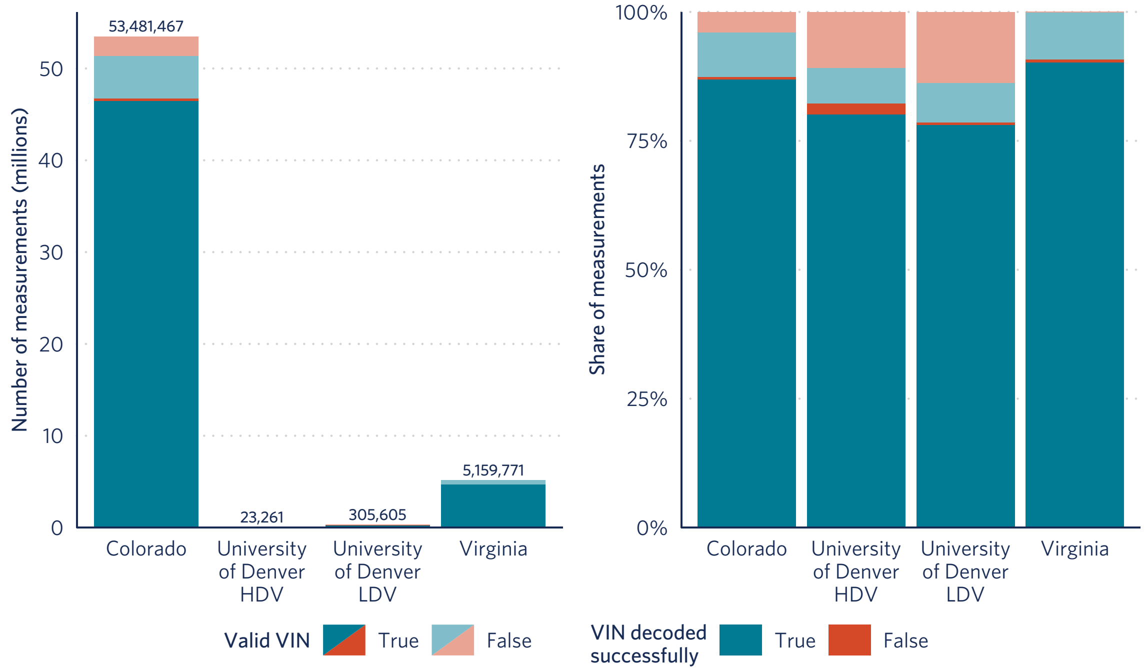


Figure 4. Number (left panel) and share (right panel) of records by data source that had valid or invalid VINs and were successfully or unsuccessfully decoded using vPIC.

(vPIC).[18] Truncated VINs—the first 11 characters less the check digit—were transmitted to the vPIC application programming interface, which returned a wide array of vehicle attributes including vehicle brand and model, model year, fuel type, vehicle type, and gross vehicle weight rating (GVWR). Select vehicle attributes from the vPIC data were stored in the TRUE U.S. database (see part D of Figure 3).

VINs play a central role in the database because all vehicle attributes are retrieved from vPIC via the VIN. Figure 4 plots the number and share of records with valid or invalid VINs, as well as the number and share of records that were successfully decoded using vPIC. The figure shows that more than 75% of measurements were associated with a valid VIN, of which the vast majority were successfully decoded using vPIC. A substantial portion of invalid VINs were also successfully decoded. Because these VINs contain errors, the vehicle attributes retrieved from vPIC may not match the vehicle measured using remote sensing, so these records were excluded from analyses.

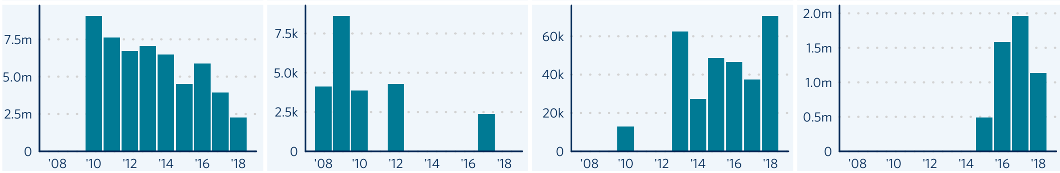
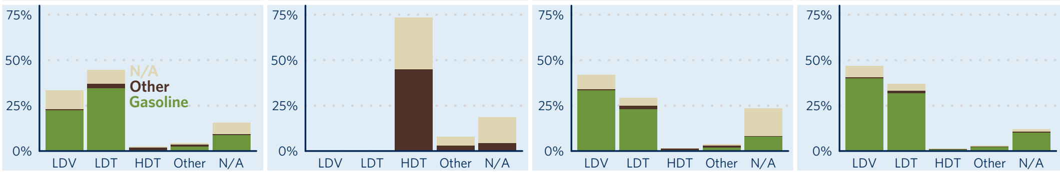
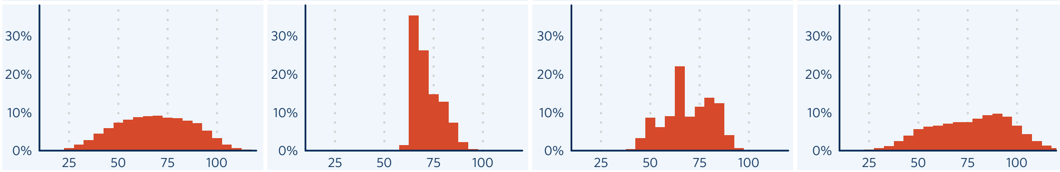
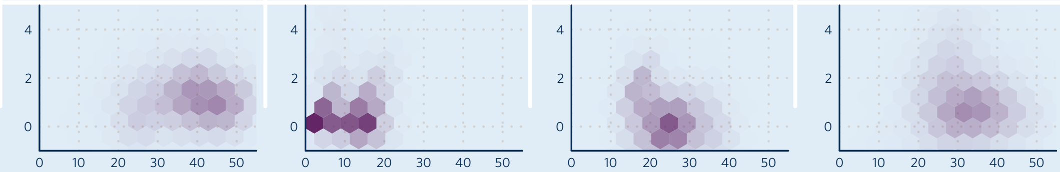
Vehicle types listed in the vPIC dataset do not match the EPA vehicle classes used in vehicle emissions standards. For example, an SUV is typically categorized as a multipurpose vehicle in the vPIC data but may be classified as a passenger car or light-duty truck in emissions standards. In order to match vehicles to emissions standards, we determined the vehicle class using the vPIC vehicle attributes. The most common vehicle classes are light-duty vehicles (passenger cars with a GVWR lower than or equal to 8,500 lb and two-wheel drive SUVs with a GVWR lower than or equal to 6,000 lb), light-duty trucks (generally pickup trucks with a GVWR less than or equal to 8,500 lb, sport utility vehicles with a GVWR less than or equal to 10,000 and with four-wheel drive or a GVWR higher than 6,000 lb, and passenger vans with a GVWR less than or equal to 10,000), and heavy-duty truck classes 2b–8 (most pickups and other trucks with a GVWR higher than 8,500 lb).[19]

Before storing remote emissions measurements in the database, measurements were examined for plausibility. Neither University of Denver nor Virginia DEQ datasets included any extreme outliers, but the Colorado data included some values that were implausible and were extreme enough to skew the means of some vehicle groups. In response, we developed physically plausible limits, while only removing a minute portion of the data

18 National Highway Traffic Safety Administration, "NHTSA Product Information Catalog and Vehicle Listing," (2020), https://vpic.nhtsa.dot.gov/.

19 Transport Policy, "US: Vehicle Definitions," (accessed April 20, 2020), https://www.transportpolicy.net/standard/us-vehicle-definitions/.

Table 1. Summary of datasets compiled in the TRUE U.S. database.

Metric	Colorado	University of Denver HDVs	University of Denver LDVs	Virginia
Number of measurements	53,481,467	23,261	305,605	5,159,771
Number of sites	195	4	8	194
States covered	CO	CA, TX	CA, CO, IL, OK, WA	VA
Instruments used	Opus RSD 4600 and 5000	DU FEAT	DU FEAT	Opus RSD 5000
Measurements per year				
Share of measurements per vehicle class and fuel type				
Ambient temperature (°F)				
Acceleration (mi/h/s) over speed (mi/h)				

Note: Vehicle class descriptions: LDV = light-duty vehicles (passenger car), LDT = light-duty trucks, HDV = heavy-duty trucks, other = all other vehicle types, N/A = no information available.

below the 0.0001th and above the 99.9999th percentile. The ranges of data retained are:

- CO: -40 to 4,000 g/kg CO_2
- HC: -20 to 2,000 g/kg CO_2
- NO: -6 to 600 g/kg CO_2

While the Virginia data and most of the DU data included road slope, the CDPHE data included road slope data for only about 7 million of the 54 million measurements, coinciding with the change to OPUS 5000-series instruments around 2015. In addition, we were able to infer the road grade for roughly an additional 14 million older records where the Opus 4000 was used at the same site as an Opus 5000.

DATABASE OVERVIEW

Remote sensing campaigns can estimate emissions under a wide range of conditions and driving, allowing an assessment of emissions by engine load, ambient temperature, and other variables. This wide coverage is a key benefit of remote sensing, and it is important to choose a variety of measurement sites to capture the whole range of driving and ambient conditions relevant to urban emissions. Table 1 summarizes the measurements, driving conditions, and sampling characteristics for the four datasets gathered from Colorado, Virginia, and the University of Denver.

The first five rows in Table 1 show the number and locations of the approximately 60 million total measurements gathered. Most of the data is from

Colorado, where remote sensing programs have been in place for close to two decades. Virginia's program was implemented more recently, but Virginia is now producing over 1 million records per year. The University of Denver datasets are much smaller, as DU conducts short-term campaigns, but add diversity in terms of geographic coverage and vehicle types such as HDVs. The total number of measurement sites is very large with almost 200 each in Virginia and Colorado, which expands the range of sampled driving conditions. While the number of measurements per year in Colorado has been slowly declining since 2010, the downward trend is exaggerated because only data for the first 6 months of 2018 was available when we collected the data.

Row 6 in Table 1 shows that the majority of records are for LDVs (cars) and LDTs, as these are the target of the Colorado and Virginia programs, and almost all LDVs and LDTs use gasoline. There are some HDV data from targeted studies conducted by DU and small amounts from Colorado and Virginia. Invalid VINs and VINs that were not able to be fully decoded or are missing some information are included in the table and account for a large portion of the N/A columns in row six. Note that the fuel type was not able to be determined for some of the records and the "other" fuel type for HDVs is predominantly diesel.

Rows 7 and 8 show that a wide range of driving conditions was captured in the remote sensing measurements. The ambient temperature distributions in row 7 show that Colorado and Virginia gather measurements throughout most of the year and reflect a broad spread in ambient temperatures from about 30°F to above 100°F, allowing investigation of the effect of ambient temperature on emissions. For each of these programs remote sensing instruments are not deployed if ambient temperatures are below roughly 30°F. Ambient temperature for the DU targeted studies aren't very normally distributed, especially for the HDV campaigns, due to being conducted during the warmer months and the comparatively small sample sizes.

Row 8 summarizes the distribution of vehicle speed and acceleration. Both the Colorado and Virginia datasets include a wide range of speed and acceleration, consistent with the large number of sampling sites in each area. The distribution of speed and acceleration is similar in Colorado and Virginia, with the largest distribution of speed being about 30 mph–50 mph in Colorado and 25 mph–45 mph in Virginia. At those speeds the largest distribution of acceleration is about 1 mph/sec–2 mph/sec acceleration in both areas, although Virginia has a wider distribution of both low and high acceleration. The speed distribution is more tightly distributed for the DU campaigns, especially for HDVs which were generally measured at low speeds at, for example, weighing stations. For LDVs, speeds measured by DU were typically 20 mph–30 mph and speeds for HDVs were less than 20 mph.

DATA ANALYSIS

As outlined in the Introduction, there are a multitude of analyses that can be done with remote sensing data. This introductory report is not intended to cover all the possible analyses. Instead, the goal is to showcase the unique capabilities of such a large collection of data using a few examples. We present four analyses, progressing from general fleet-level assessment to analysis of individual vehicles.

LONG-TERM LDV EMISSION TRENDS

Figure 5 summarizes CO, HC, and NO emission trends by model year for gasoline LDVs and LDTs. Note that the vehicles were sampled from 2010 to 2018 for the Colorado and DU studies and from 2015 to 2018 for the Virginia studies, so the average for each model year includes vehicles of different ages. The 2019 model year (MY) vehicles were removed due to their small sample size (<100). Mean fuel-specific (gram emissions per kg fuel consumed) emission factors and 95% confidence intervals are presented for each data source. The large Virginia and Colorado sample sizes means that the 95% confidence intervals are very small for these trend lines. The respective phase-ins of the EPA emission standards are also indicated on the graphs.

The three different data sets show general agreement on the dramatic downward trend in fleet-average emissions for each pollutant with model year. Emissions are particularly low after the phase-in of the Tier 2 standards, showcasing the improvements caused by the implementation of more stringent emission standards for light-duty vehicles and trucks in the United States. This example shows how large collections of remote sensing data, collected over many years, can be used to track the real-world effectiveness of policy and technology developments in reducing vehicle emissions.

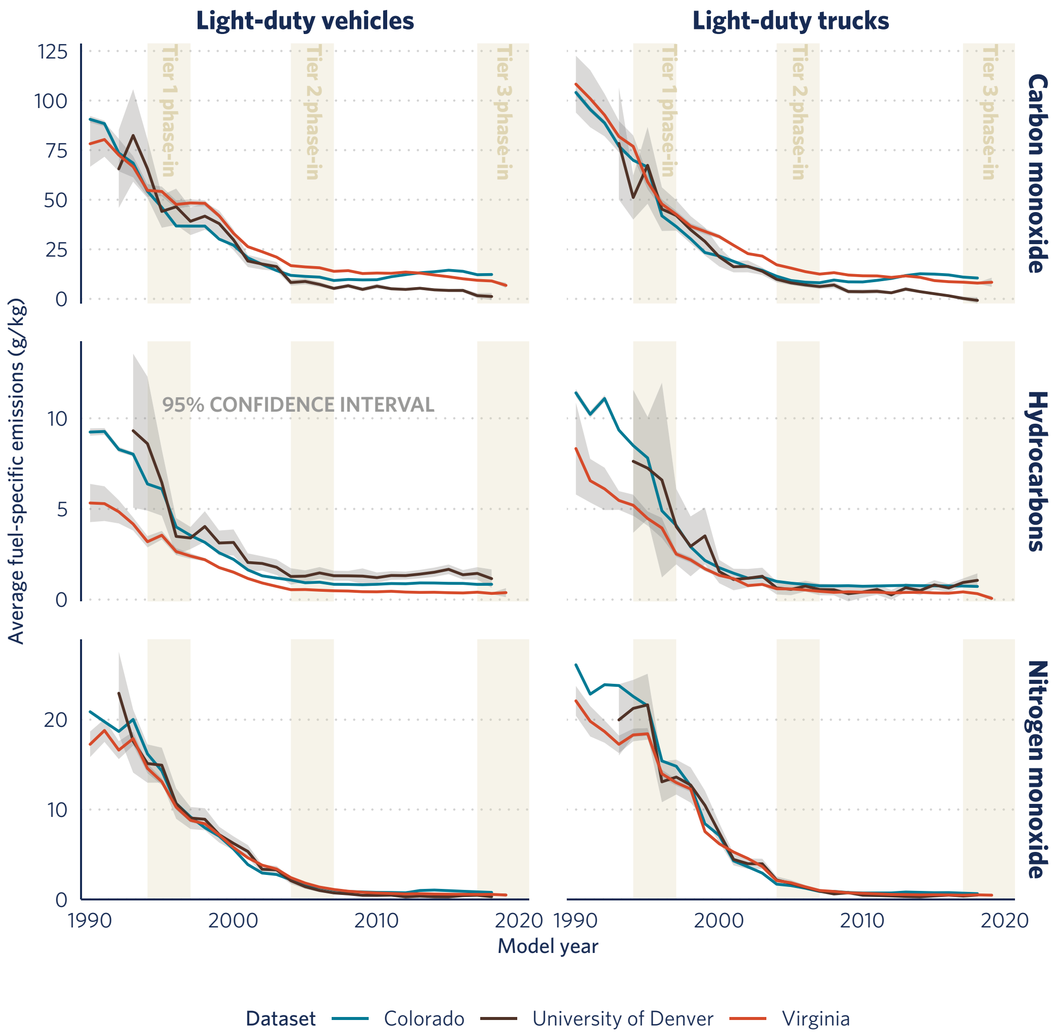


Figure 5. Average fuel-specific pollutant emissions (g/kg fuel) of gasoline light-duty vehicles by vehicle class and data source.

INFLUENCE OF VEHICLE AGE ON EMISSIONS

Our second example illustrates the ability to use remote sensing to analyze the impact of vehicle age on emissions. Remote sensing is ideally suited for this analysis due to its ability to collect data on large amounts of vehicles and track the vehicle emissions performance of each model year over time. In theory, the TRUE U.S. database is ideal for measuring deterioration trends because of its vast size and geographical and temporal coverage. Here, we use Colorado NO data to present a high-level example of how remote sensing data can be used to investigate deterioration trends.

Figure 6 shows the average fuel-specific (g/kg fuel) NO emissions for gasoline cars and light trucks by model year and age in Colorado. NO emissions of all model years and both vehicle classes increase with vehicle age. The trend is more pronounced for older model years, for which the deterioration rate can exceed 0.2 g NO/kg fuel per year. Vehicles meeting the Tier 2 emission standards, roughly model years 2007–2015, exhibit rates ranging from 0.06 g to 0.12 g NO/kg fuel per year. Provided these deterioration rates can be extrapolated in a linear fashion, these rates indicate an increase in emissions of 0.6 g/kg–1.2 g/kg over a ten-year period, the full useful life defined in the EPA Tier 2 emissions standards. Across these model years, this represents an approximate median increase in emissions of 200% during the EPA defined useful life period. A more detailed treatment of emissions deterioration, including

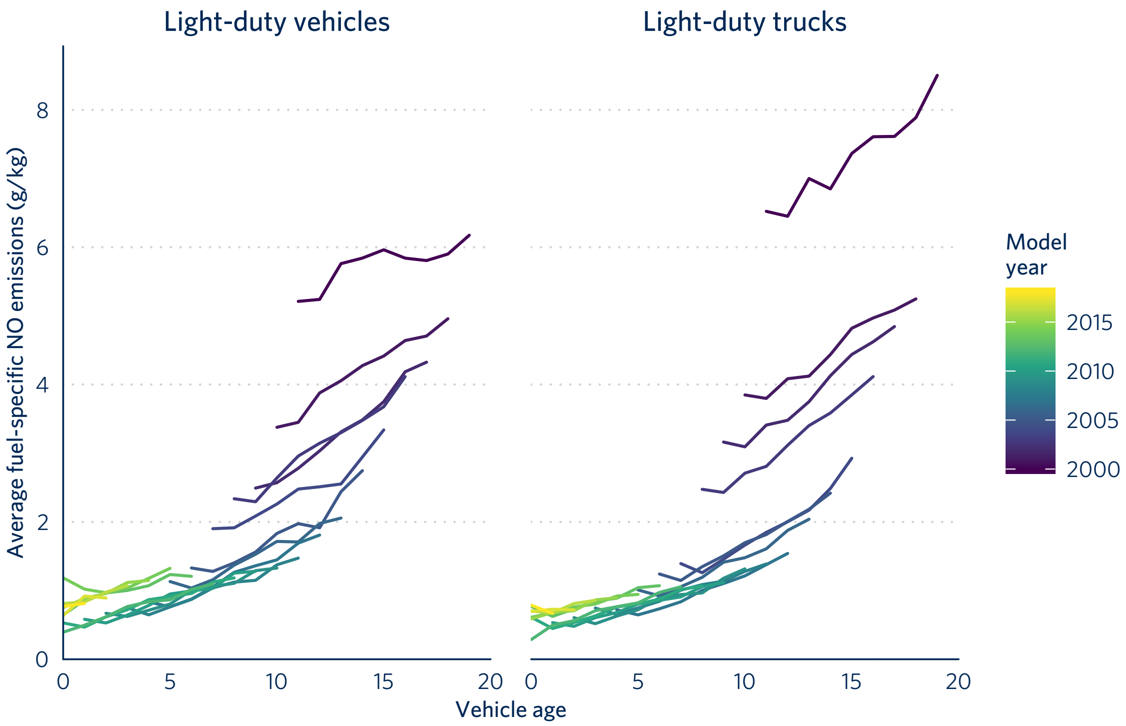


Figure 6. Average fuel-specific NO emissions of gasoline light-duty vehicles and light-duty trucks per model year and vehicle age.

comparisons with manufacturer-reported deterioration rates, can be found in an accompanying case study.[20]

Of course, the remote sensing data do not identify the cause of the emission increase, which could be a combination of emission control system deterioration, emission component defects, an increasing number of unrepaired malfunctions, or tampering. As manufacturers are responsible for emission control system deterioration, but not for malfunctions or tampering, it is important to distinguish between them. Malfunctions and tampering can only be identified by tracking individual vehicles over time, as illustrated by our fourth example, below.

IDENTIFICATION OF HIGH-EMITTING VEHICLE GROUPS

The third analysis explores ways in which remote sensing data can be used to identify high-emitting vehicle groups and anomalous real-world emissions behavior. For this example, we switch from gasoline to diesel engines and focus on three popular pickup truck models. These include models from Dodge/Ram (2500 and 3500), Ford (F250 and F350), and Chevrolet (Silverado 2500 and 3500), all with similar size diesel engines between 6.4 and 6.7 liters and certified as class 2b and class 3 heavy-duty vehicles.

Figure 7 shows the average monthly fuel-specific (g/kg fuel) NO emissions for each of the three manufacturers over each of the 2010 to 2015 model years, with class 2b and class 3 emissions presented separately. Only monthly averages with at least 30 measurements are included in the figure and the number of measurements for each point are indicated by the size of the marker. Note that Ford used a 6.4L engine in 2010 and switched to a 6.7L engine in MY 2011.

For MY 2010, NO emissions from Chevrolet trucks are significantly higher than those from trucks produced by the other manufacturers, though data are relatively scarce for this group (note the absence of class 3 results). NO emissions are reduced in later model years, with MY 2011-2015 Chevrolet trucks exhibiting the lowest emissions for each model year, on average, among the three manufacturers.

The Ram 2500 and 3500 trucks included in this sample have been subject to a number of emissions-related recalls. These include recalls for MY 2010 and MY 2012 vehicles related to software errors and engine

20 *Emissions deterioration of U.S. gasoline light-duty vehicles and trucks*, https://theicct.org/publications/true-us-database-emissions-deterioration-oct2020.

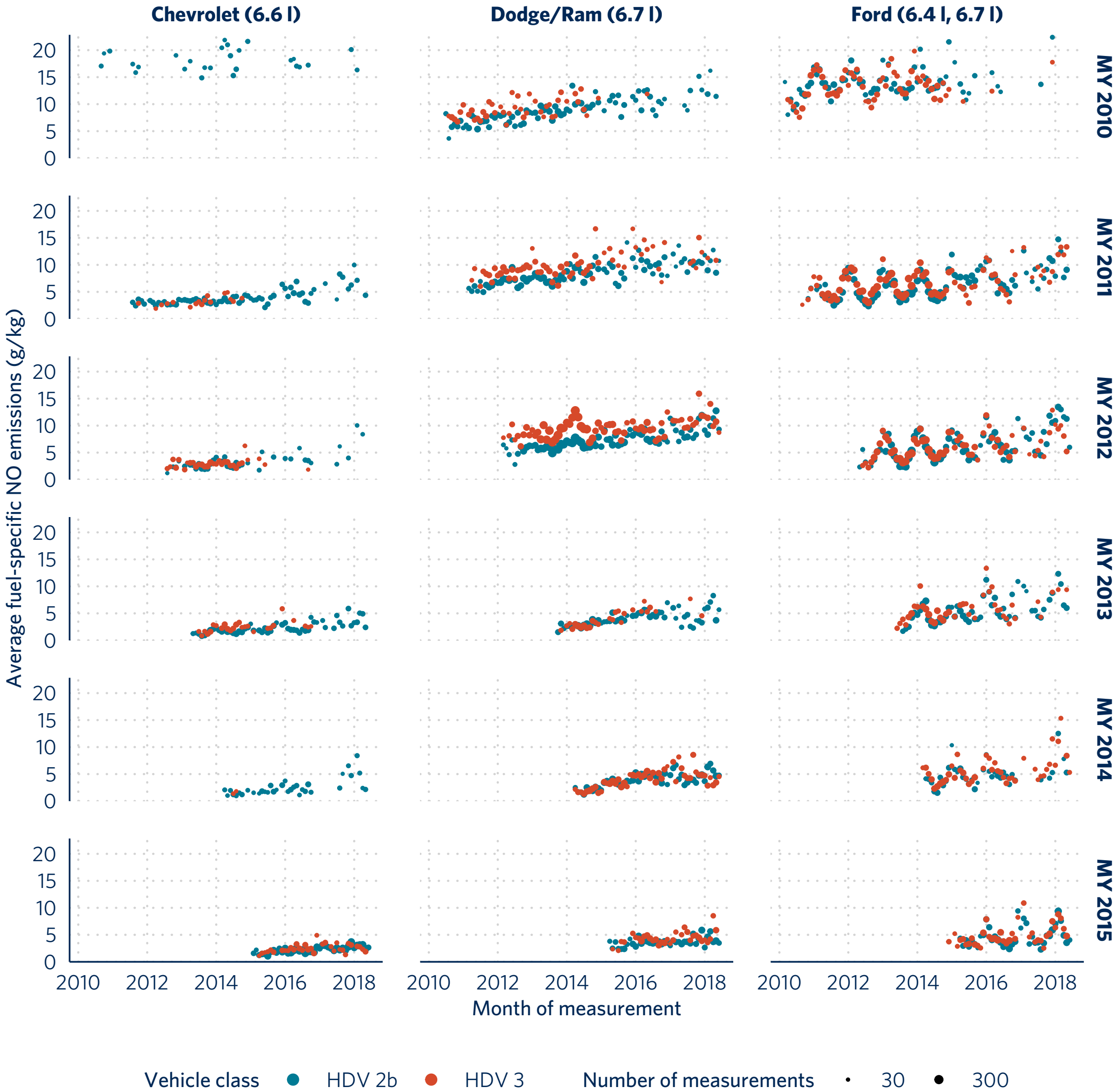


Figure 7. Average monthly fuel-specific NO emissions of three manufacturers and six model years of class 2b and class 3 diesel trucks.

calibrations, respectively, that can lead to high in-use NO_x emissions.[21] Approximately 85% of MY 2010 and 36% of MY 2012 trucks in our sample were impacted by these recalls.[22] Furthermore, MY 2013–2015 Ram trucks use a Cummins 6.7L diesel engine that has been recalled due to a defective emission control system. Selective catalytic reduction (SCR) systems were found to degrade within a few years instead of controlling emissions throughout the engine's full useful life, leading to excessive NO_x emissions.[23] In our sample, 85% of MY 2013-2015 Ram trucks were subject to recalls related to degradation of the SCR system.

For MY 2011 and MY 2012, the Ram emissions are both higher and have a higher deterioration rate with age than the other makes. Emissions of MY 2013-2015 vehicles are improved relative to MY 2010-2012 trucks, though deterioration rates are of similar magnitude and may be an indication of accelerated SCR degradation. Durability issues become more apparent as vehicles age, as poor-quality components that deteriorate more rapidly than expected may still be reasonably effective for a few years.

21 Chrysler, "Emissions recall K34," accessed June 15, 2020, https://www.chrysler.com/universal/webselfservice/pdf/K34.pdf.
Fiat Chrysler Automobiles, "Emissions recall T05," accessed June 15, 2020, https://www.chrysler.com/universal/webselfservice/pdf/T05.pdf.

22 Mopar, "Recall information," accessed June 15, 2020, https://www.mopar.com/en-us/my-vehicle/recalls/search.html

23 TruckStop, "Truck & Bus Regulation," accessed May 20, 2020, https://ww3.arb.ca.gov/msprog/truckstop/tb/truckbus.html.

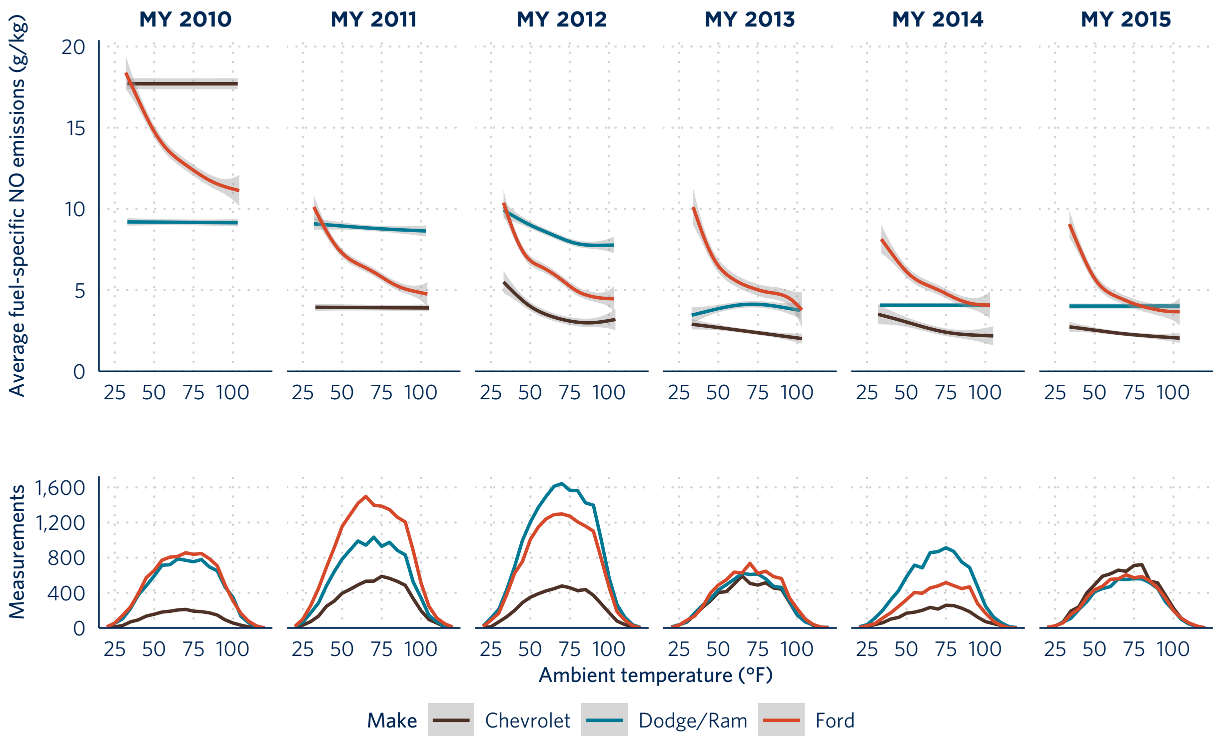


Figure 8. Top graphs: Fuel-specific NO emissions of class 2b and class 3 diesel trucks by model year and make as a function of ambient temperature. The relationship between NO emissions and ambient temperature are represented using generalized additive models with 95% confidence intervals. Bottom graphs: Number of measurements for each make (bin width: 5 °F).

Perhaps the most interesting feature of Figure 7 is the clear seasonal variation in the level of NO emissions from Ford F250 and F350 trucks. This trend of the highest emissions observed in colder winter months and comparatively lower emissions during warmer summer months is apparent in the data for each model year and vehicle class considered in the analysis. Notably, similar seasonal trends are not observed in the data for similar vehicles from the other two manufacturers.

Because Figure 7 reveals seasonal fluctuations in NO emissions from Ford trucks, Figure 8 explores the relationship between NO emissions and ambient temperature.[24] The ambient temperature range is truncated, from the 2nd to 98th percentile per group, to avoid plotting the relationship for ranges with scarce data.

24 Generalized additive models, as implemented in the mgcv and ggplot packages for the R software environment, were used to plot the relationship between NO and ambient temperature. See: Simon N. Wood, Fast Stable Restricted Maximum Likelihood and Marginal Likelihood Estimation of Semiparametric Generalized Linear Models: Estimation of Semiparametric Generalized Linear Models, *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 73, no. 1 (January 2011): 3–36, https://doi.org/10.1111/j.1467-9868.2010.00749.x; Hadley Wickham, *Ggplot2: Elegant Graphics for Data Analysis - Rev 2016*, Use R! (Cham: Springer International Publishing, 2016), https://doi.org/10.1007/978-3-319-24277-4; R Core Team, "R: A Language and Environment for Statistical Computing" (Vienna, Austria: R Foundation for Statistical Computing, 2020), http://www.R-project.org/.

The results indicate that all model years of Ford vehicles exhibit a dependency between NO emissions and ambient temperature. Emissions from Ford vehicles increase by approximately 5 g NO/kg when comparing the high end of the temperature range (approximately 100 °F) to the low end (approximately 30 °F). Neither Chevrolet nor Dodge/Ram class 2b and 3 diesel trucks exhibit a consistent effect of ambient temperature on NO emissions. The near doubling of NO emissions from the Ford vehicles in cold weather conditions indicates an emission control system calibration change and warrants further investigation.

IDENTIFICATION OF INDIVIDUAL HIGH-EMITTING VEHICLES

The final showcase focuses in on the data even further and plots trends in individual vehicles from the preceding figure to demonstrate the value of large-scale, long-term collection of remote sensing data. As for the preceding examples, the data was filtered for valid VIN and valid NO measurements.

There are a large number of individual vehicles in the remote sensing data. To maximize the usefulness of the data, vehicles and data were filtered to include:

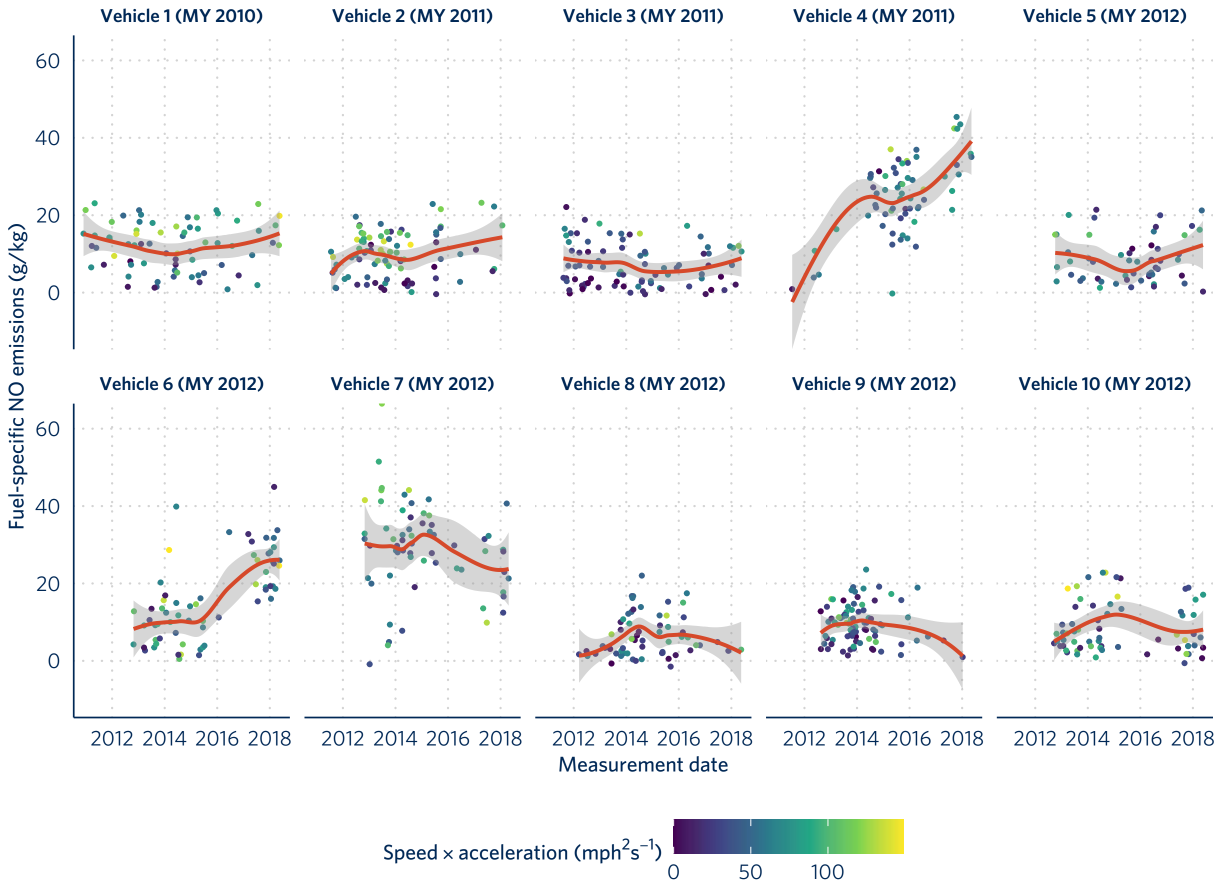


Figure 9. Fuel-specific NO emissions of individual Dodge/Ram 3500 vehicles with more than 50 measurements and at least one measurement per year.

- only RAM 3500 class 3 HDVs from the 2010 to 2012 model years.
- at least 50 total measurements for each individual vehicle.
- at least one measurement for each year since the model year. For example, a MY 2010 vehicle must have at least one measurement for each year from 2010 to 2018.
- velocity times acceleration (VxA) between 0 and 150 mph^2/s in order to exclude idling and extreme high engine load events.

Figure 9 plots the NO emissions by vehicle age for all ten individual vehicles that met the filtering criteria. Locally estimated scatterplot smoothing (LOESS) was used to highlight the central tendency in the data for each vehicle. Interestingly, seven of the ten vehicles do not show large increases in NO emissions with vehicle age. However, vehicles 4 (MY 2011) and 6 (MY 2012) have drastic increases, with vehicle 4 increasing from near zero to almost 40 g/kg and vehicle 6 increasing from about 10 g/kg to about 30 g/kg. Vehicle 7 has elevated emissions from the first measurements when the truck was almost new, which is difficult to understand unless the vehicle was defective to begin with.

CONCLUSIONS AND RECOMMENDATIONS

Remote sensing has a number of important characteristics that make it a particularly good tool for market surveillance. These include the ability to measure a large number of vehicles in a relatively short period of time, the ability to measure the emissions of in-use vehicles, its non-intrusiveness to traffic flow and vehicle operation, and the ability to monitor older as well as newer vehicles at relatively low cost.

The primary purpose of this project is to investigate ways in which remote sensing data collected in the United States can be used to further understanding of real-world vehicle emissions and support the development of evidence-based emissions control policies and actions. In addition to presenting summary statistics of the different datasets from the states of Colorado and Virginia and the University of Denver, this report presented brief examples of how the data could be analyzed, including evaluation of long-term emission trends, tracking emission changes as vehicles age, investigation of high-emitting vehicle groups, and evaluation of individual vehicle emissions performance.

To help local areas achieve their air quality goals, it is essential to better understand the causes of the high real-world emissions. Remote sensing campaigns continue to find that real-world emissions can be much higher than emission standards. The problem is compounded as manufacturers are responsible for normal deterioration and emission defects but not for malfunctions and tampering. Policy recommendations to maximize the potential of remote sensing include:

- Increased government investment in remote sensing to identify the causes of high real-world emissions. This includes greater geographic coverage and a wider variety of operating conditions.
- Expanded use of remote sensing data in decision making and policy development.
- Expanded use of remote sensing programs to support manufacturer surveillance activities.
- Exploring ways remote sensing could be used to increase repairs of malfunctions and to improve tampering enforcement.

This report is just the first step in an ongoing process to gather and analyze remote sensing data, as part of the TRUE initiative. Specific recommendations for future database development are:

- Update the dataset with most recent data from Virginia and Colorado (through 2019).
- Add additional data sources.
- Add emission standard classification data. The current datasets do not include definition of the emission standard Tier or bin to which the vehicle has been certified. Adding such information is not a trivial task, as the remote sensing database would need to be merged with emission data files from the EPA.

Three case studies accompany the publication of this report. The topics of these studies are:

- **Emissions deterioration of U.S. gasoline light-duty vehicles and trucks.** This expands upon the analysis above of vehicle emissions by age, adding the Virginia data and analyzing all emissions, not just NO.
- **Remote sensing of heavy-duty vehicle emissions in the United States.** This case study focuses on analyzing data for Class 5-8 HD trucks included in the database, including an assessment of NOx emission trends by model year and the impacts of driving conditions on emissions.
- **Emissions distributions by vehicle age and policy implications.** This case study quantifies emissions distributions to investigate the contributions of the oldest LDV and HDV vehicles in fleets to total emissions and what this may mean for the effectiveness of city-level emission control policies.

Other opportunities for analyses include whether the distribution of remote sensing measurements by model year and age matches estimates of vehicle scrappage rates and miles driven by vehicle age, emissions from taxis and other high-usage fleets, how emissions from gasoline direct engines compare to port fuel injection engines, and whether malfunctions and tampering of individual vehicles can be reliably identified. In addition, the TRUE U.S. database can be analyzed together with similar European databases to shed light on regional differences in real-world emissions performance.

Related case studies:

"Emissions deterioration of U.S. gasoline light-duty vehicles and trucks"
https://theicct.org/publications/true-us-databaseemissions-deterioration-oct2020

"Remote sensing of heavy-duty vehicle emissions in the United States"
https://theicct.org/publications/true-us-database-hdvemissions-oct2020

"Emissions distributions by vehicle age and policy implications"
https://theicct.org/publications/true-us-database-emissions-distribution-oct2020

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