# Appendix: Union of Concerned Scientists Methodology to Assess Truck Emissions for Different Technologies

## Truck Emissions

Trucks powered by fossil fuel combustion directly emit pollution from the tailpipe. However, in thinking through the total impact of these vehicles, it is important to also consider the impacts of the fossil fuel infrastructure supporting these vehicles—there are emissions associated with the refining of petroleum into gasoline or diesel fuels, and there are emissions also associated with the obtaining that petroleum feedstock in the first place.

Electric trucks do not directly emit any tailpipe pollution, but there are emissions associated with the production of electricity needed to power these trucks. There are also emissions associated with the provision of fuel for the electricity grid. Liquid and gaseous fuels also have upstream emissions associated with extraction, refining, distribution, and more that also need to be considered when assessing the total impact of different technologies.

For the most apples-to-apples comparison between vehicles, emissions and impacts from all three phases of the lifecycle are considered, in total: 1) feedstock; 2) fuel; and 3) use. For upstream emissions from fuel and feedstock, this data is generally obtained from the latest version of Argonne National Lab's (ANL's) "Greenhouse gases, Regulated Emissions, and Energy use in Technologies" (GREET) Model (2022). Direct emissions from use are further discussed below. In assessing the impact of these technologies, we consider emissions produced over the expected lifetime usage of the vehicle, which includes degradation of the emissions controls over time.

## Heavy-duty Truck Characteristics

Heavy-duty trucks come in a range of vehicle sizes and weights and undergo a wide range of operation. To capture typical behaviors of interest, we consider a representative list of vehicle classes and duty cycles (Table 1).

### *Duty cycle*

To best match real-world performance, we relied almost entirely on representative duty cycles from the National Renewable Energy Lab (NREL), primarily that collected as part of its FleetDNA program, which uses real-world data to generate a representative test cycle (NREL 2022). There are two exceptions, one for school buses and another for refuse trucks. While FleetDNA data is available for these cycles, there is not a single representative duty cycle published, so we designed our own to best match the available test data by breaking representative cycles into microtrip segments and combining in ratios that matched the duty cycle statistics of the Fleet DNA dataset. In the case of school buses, this combined three representative cycles identified by NREL, the Orange County Transit Bus Cycle (OCTA), CARB Heavy-heavy Duty Transient Combined Cycle (HHDDT), and the Rowan University Composite School Bus Cycle (RUCSBC) (Duran and Walkowicz 2013). For the refuse truck, we combined two different refuse truck cycles for different refuse types, the NREL Miami-Dade Refuse Cycle (developed by NREL from automated side-loader refuse truck data from vehicles operated by Public Works and Waste Management in Miami-Dade County, Florida) and the NREL Neighborhood Refuse Cycle (developed with EPA as part of the Smartway program, representing automated side-loader refuse truck operation) with the Braunschweig city driving cycle, a low-speed transient driving schedule with frequent stops.

**TABLE 1.** Heavy-duty vehicle classes, types, and duty cycles

| Vehicle Class | Vehicle Type | Duty Cycle |
|---|---|---|
| Class 4 | Delivery Van | FleetDNA (Local Delivery, Representative) |
| Class 6 | Delivery Truck | FleetDNA (Local Delivery, Representative) |
| Class 6 | School Bus | Test cycle matching NREL School Bus Data |
| Class 8 | Refuse Truck | Test cycle matching NREL FleetDNA Refuse Truck data |
| Class 8 | Tractor (Drayage) | FleetDNA (Drayage, Representative) |
| Class 8 | Tractor (Regional) | FleetDNA (Regional-Haul, Representative) |
| Class 8 | Tractor (Line-Haul) | FleetDNA (Long-Haul, Representative) |
| Class 8 | Transit Bus | FleetDNA (Transit Bus, Representative) |

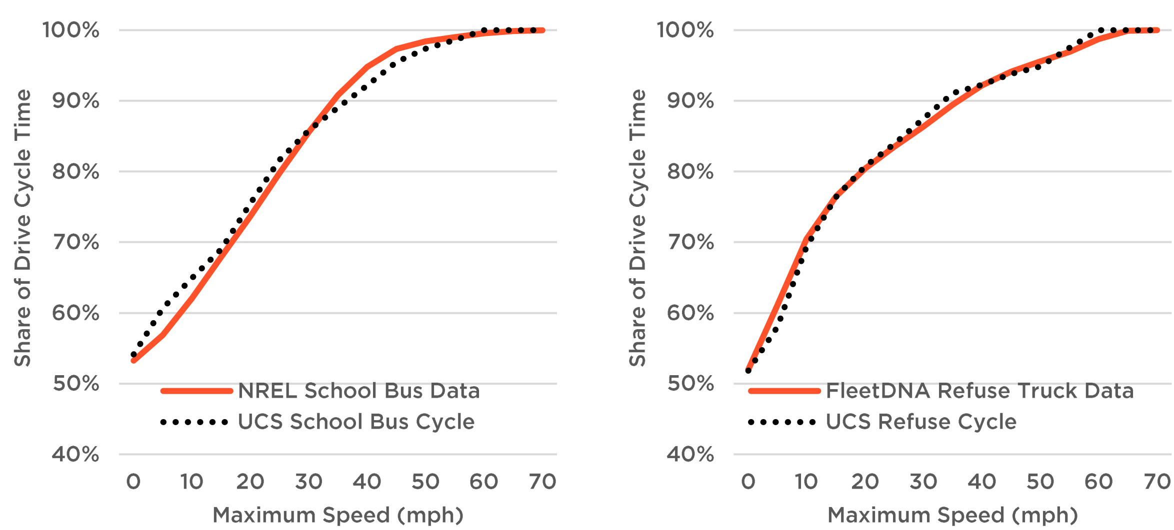
*To best match real-world performance, we have relied on duty cycle data collected in the real world by NREL, primarily through its FleetDNA program.*

**TABLE 2.** Comparison between UCS-generated duty cycles and NREL FleetDNA data

| | School Bus | | Refuse Truck | |
|---|---|---|---|---|
| Cycle Characteristic | UCS | FleetDNA | UCS | FleetDNA |
| Characteristic Acceleration ($ft/s^2$) | 0.69 | 0.63 ± 0.10 | 0.71 | 0.50 ± 0.12 |
| Aerodynamic Speed (ft/s) | 52.7 | 47.6 ± 8.8 | 55.4 | 48.9 ± 9.5 |
| Kinetic Intensity (1/mile) | 1.32 | 1.63 ± 0.66 | 1.22 | 1.11 ± 0.50 |
| Average Driving Speed (mph) | 23.1 | 23.3 ± 4.0 | 20.6 | 20.7 ± 6.5 |
| Stops per Mile | 2.66 | 1.73 ± 0.61 | 10.04 | 4.01 ± 3.18 |
| Stops per Minute | 0.47 | 0.34 ± 0.12 | 1.66 | 0.66 ± 0.34 |

*Utilizing a combination of vocational duty cycles allowed us to match well NREL-collected data on school buses and refuse trucks.*

**FIGURE 1.** Comparison of speed bin data for UCS data cycles and NREL-collected data for school buses and refuse trucks




*A profile of speed bin data for school buses and refuse trucks collected by the National Renewable Energy Lab (NREL) and the duty cycle generated by UCS for use in this report affirm the representativeness of the UCS duty cycles for these vocations.*

Additional idle time was also added as needed in between zero-to-zero microtrips.[1] A comparison of the UCS-derived cycles and the FleetDNA data is shown in Table 2 and Figure 1.

Unlike the other vehicles listed in Table 1, refuse trucks spend a significant amount of fuel use through power-take-off (PTO), in this case while the vehicle is compacting trash. Real-world data shows that a significant amount of operation time is spent at idle, during which the PTO is operational, and one study showed that 30 percent of fuel energy went towards operation of the compactor (Wysocki et al. 2018). However, due to limited data and the use of GEM (detailed below) to assess fuel consumption, this analysis solely assigns fuel consumption rates based on the duty cycle data.

### *Vehicle characteristics*

In order to have a systemic approach to the operational characteristics of the different vehicles, we rely on modeling originally built to supporting EPA and NHTSA's Phase 2 Greenhouse Gas Emissions and Fuel Economy Standards.[2] Vehicle characteristics were determined by the final stringency required under those regulations, based on a regulatory category corresponding to each vehicle type (Table 3). Because the final regulatory category is based on an average fleet mix of characteristics (i.e., in most cases stringency was not predicated on a single technology package but on an assumed mix of technology packages), a given vehicle's technology package was determined based on the mix of technology features needed to most closely match the average characteristics of the vehicle class. To the extent there are lingering errors, those differences were assessed in a way to ensure that the fuel economy of the diesel vehicle would match or exceed that required under the regulatory cycle.

**TABLE 3.** Heavy-duty vehicle types assigned to EPA regulatory classes

| Vehicle Class | Vehicle Type | EPA Regulatory Class |
|---|---|---|
| Class 4 | Delivery Van | LHD-Urban (Vocational) |
| Class 6 | Delivery Truck | MHD-Urban (Vocational) |
| Class 6 | School Bus | School Bus (Custom Chassis) |
| Class 8 | Refuse Truck | Refuse Truck (Custom Chassis) |
| Class 8 | Tractor (Drayage) | Class 8 High-roof Day Cab (Tractor) |
| Class 8 | Tractor (Regional) | Class 8 High-roof Day Cab (Tractor) |
| Class 8 | Tractor (Line-Haul) | Class 8 High-roof Sleeper Cab (Tractor) |
| Class 8 | Transit Bus | Transit Bus (Custom Chassis) |

*EPA regulatory classes align well with the vehicle categories studied in this analysis.*

Both electric trucks and combustion engine-powered trucks are likely to improve in efficiency in the coming years. New trucks are required to meet fuel economy and greenhouse gas emissions standards through at least 2029, predicated predominantly on the increased efficiency of combustion engine-powered vehicles. The level of ambition of those targets based on EPA's judgment was reiterated in a recent rulemaking, where EPA stressed that it had "set the existing [heavy-duty (HD) greenhouse gas (GHG)] Phase 2 standards at levels that would require *all* [emphasis added] conventional vehicles to

[1] Unlike the FleetDNA representative cycles, these drive cycles did not have key on/off or grade information. To determine this, we applied the EPA grade profile used in the Phase 2 Greenhouse Gas Regulations (in whole number steps to ensure symmetric uphill/downhill profile and assumed key-off park after 90 seconds of idle.
[2] Since the Phase 2 rulemaking, the agency's Greenhouse gas Emissions Model (GEM) has been updated multiple times. We utilize the latest version of the model (4.0), available at https://www.epa.gov/regulations-emissions-vehicles-and-engines/greenhouse-gas-emissions-model-gem-medium-and-heavy-duty.

install varying combinations of emission-control technologies…. The HD GHG Phase 2 standards were based on adoption rates for technologies in technology packages that EPA regards as appropriate under [the Clean Air Act] section 202(a) for the reasons given in the HD GHG Phase 2 rulemaking." (87 FR 17440-1).

A number of new technologies have been developed since the Phase 2 rules were finalized, including some like cylinder deactivation which could aid manufacturers in compliance with new $NO_X$ emissions tandards as well as reduce fuel use and greenhouse gas emissions. One study shows as much as a one-third further reduction possible in fuel use from conventional trucks by 2035 (ICCT 2021). However, the vast majority of these reductions come from advancements in technology that would be directly applicable to electric truck efficiency as well (tires, axle efficiency, aero, weight reduction). Because such differences would affect both classes of vehicle in this study but have no known schedule of likely deployment in the absence of future regulation, we have not assumed any additional improvement for conventional trucks beyond what the Phase 2 standards require.

For electric trucks, no improvements in efficiency were assumed. This conservative assumption was chosen to account for the uncertainty in how future improvements to batteries and power electronics would manifest themselves in next-generation electric trucks—for example, improvements in battery cell density may be used to increase the vehicle's range rather than reduce weight, which could then be used to improve freight efficiency. In the case of long-haul electric trucks, it is likely that all such improvements would be applied to increasing the range of the vehicle—while long-haul is a shrinking slice of the truck market (NACFE 2019), a major reason for the lack of availability of a long-range electric truck is the impact of weight on payload using today's current battery technology, though manufacturers have already increased range on the few Class 8 electric tractors on the market and will likely continue to do so (Volvo 2022).

## Greenhouse Gas Emissions and Fuel Usage

Greenhouse gas emissions for conventional diesel-powered vehicles are directly related to the fuel used throughout the duty cycle of those vehicles. Because diesel fuel is a widely distributed commodity and the entire nation has adopted the same low-sulfur diesel fuel standards, a single national average fuel energy density and upstream emissions profile was chosen.

In contrast, greenhouse gas emissions for electric trucks are dependent upon the electric grid powering them, which makes them much more geographically dependent. The upstream emissions associated with the electric grid (and the associated assumptions) are discussed in much greater detail later in the report.

Below, the methodology to assess the efficiency of the two types of vehicles is described in greater detail.

### *Combustion-engine Vehicles and Fuel Economy*

Given the wide range of operating conditions, it is critical to establish a consistent framework for assessing the expected fuel usage for diesel-powered trucks. In this case, we utilize the latest version (Phase 2 v4.0) of the Greenhouse gas Emissions Model (GEM) designed by EPA to assess the appropriateness of its greenhouse gas emissions program and measure compliance with that program.

Phase 2 GEM is a physics-based simulation of a heavy-duty truck, modeled in MATLAB using Simulink with Stateflow. There are four submodules governing the simulation: 1) Ambient subsystem, which establishes road grade, temperature, etc.; 2) Driver subsystem, which is a time-based controlling module that attempts to match a given duty cycle, with some look-ahead; 3) Powertrain subsystem, which includes the engine, transmission, electric accessories, and driveline; and 4) Vehicle subsystem, which consists of the chassis and relevant physical forces on the vehicle related to aerodynamic drag, rolling resistance, etc.

Rather than simulating the fuel used by the vehicles through the regulatory cycles, we used the representative duty cycles outlined above to assess fuel usage, including regulatory payload, tires, etc. The fuel economy for each vehicle based on features needed for each regulatory class to meet the 2021 and 2027 GHG standards is shown in Table 4.

**TABLE 4.** GEM-simulated fuel economy on both the representative duty cycle and regulatory test cycles

| Reg Class | Vehicle Type | Representative Fuel Economy (mpg-diesel) | | GEM Regulatory Cycle Result (g/ton-mile) | | GEM Regulatory Standard (g/ton-mile) | |
|---|---|---|---|---|---|---|---|
| | | 2021 | 2027 | 2021 | 2027 | 2021 | 2027 |
| LHD-U | Delivery Van | 10.1 | 10.9 | 422 | 375 | 422 | 375 |
| MHD-U | Delivery Truck | 7.1 | 7.6 | 295 | 265 | 295 | 265 |
| Custom (School Bus) | School Bus | 5.5 | 6.2 | 298 | 268 | 298* | 271 |
| Custom (Refuse) | Refuse Truck | 3.2 | 3.6 | 323 | 292 | 323* | 298 |
| C8 Day Cab – HR | Tractor (Drayage) | 4.9 | 5.3 | 85.6 | 75.7 | 85.6 | 75.7 |
| C8 Day Cab – HR | Tractor (Regional) | 6.4 | 7.3 | 85.6 | 75.7 | 85.6 | 75.7 |
| C8 Sleeper Cab – HR | Tractor (Line-Haul) | 6.9 | 8.1 | 75.7 | 64.3 | 75.7 | 64.3 |
| Custom (Other Bus) | Transit Bus | 4.4 | 4.7 | 302 | 270 | 302* | 286 |

*Despite matching well the greenhouse gas emissions standards on the test cycle, as simulated in GEM, the fuel economy for diesel-powered trucks remains quite low through 2027 in the identified applications, owing to intense duty cycles.*

*NOTE: Because the simplified GEM model used for compliance utilizes a 2027-model year engine map rather than the engine map associated with the vehicle, the regulatory standards for the custom chassis vehicles for 2021 are compared to the vocational standard (e.g., MHD-U) rather than the custom chassis standard for 2021-2026.

In addition to diesel-fueled vehicles, we considered both hydrogen and natural gas combustion engines as well. Natural gas trucks are expected to see a 5 to 15 percent energy deficiency compared to diesel engines, dependent upon the engine configuration (Chapter 13, EPA 420-R-16-900); however, given the increased emissions control requirements for diesel and the lack of an adequate natural gas engine map, we opted for the conservative estimate of energy-equivalent efficiency. Similarly, there is little data on hydrogen combustion engines, and the efficiency of those engines is dependent upon unknown characteristics of untested powertrains, so we assumed (again, conservatively) energy-equivalence for $H_2$ICEVs as well.

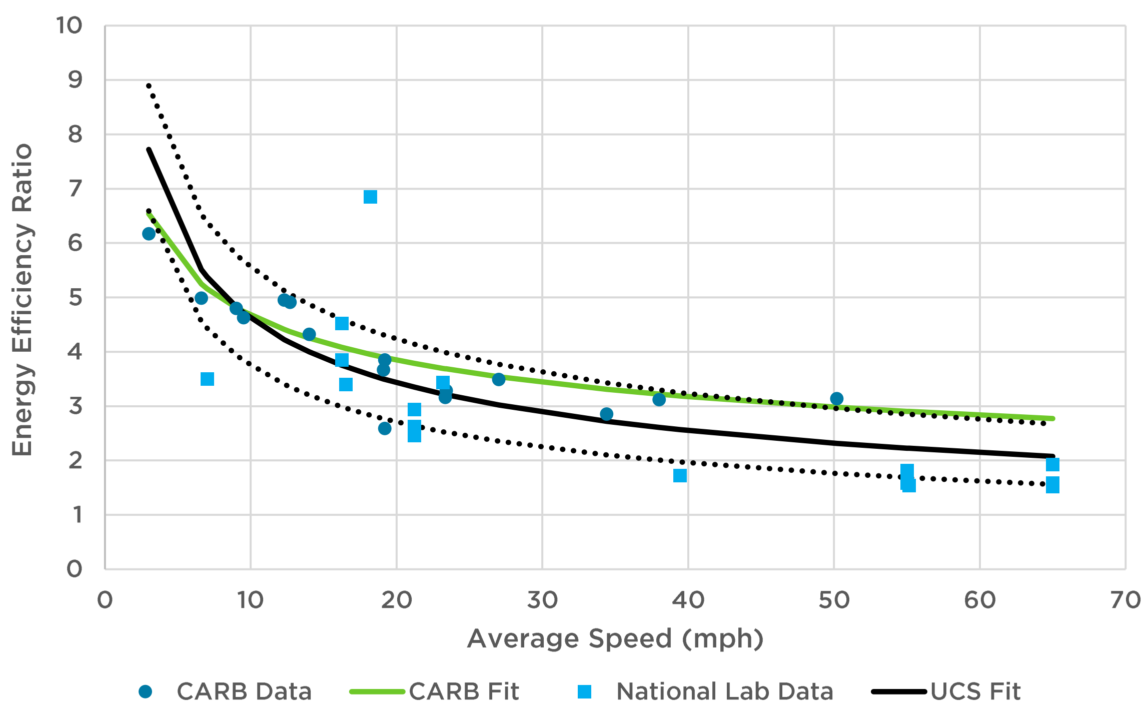
### *Electric Vehicles and Energy Efficiency*

More than half of the energy contained in diesel fuel is wasted in the combustion process of a diesel truck (DOE 2013, Figure 5). In contrast, electric motors can be 90 percent efficient or more (DOE 2016, Figure 8.E.3). Electrification thus presents a tremendous opportunity for improving the efficiency of the trucking sector.

Efficiency gains can be further improved in duty cycles where there is significant braking, since electric trucks can use regenerative braking to limit energy wasted in the form of heat. Clearly such an opportunity varies widely among applications, and previous studies on hybrid-electric trucks showed that the relative advantages could be characterized exclusively by a few parameters specific to a given duty cycle (O'Keefe et al. 2008). Below, we walk through a simple model for the advantage of fully electric trucks.

Given the relatively small (but growing!) number of electric trucks on the road today, there is scant data on real-world efficiencies. Early data from the California Air Resources Board showed that the efficiency improvement of electric trucks over their diesel counterparts could largely be considered as to the average speed of their duty cycle (CARB 2018). Additional modeling data compiled by two different national labs can help fill in some of the gaps in the CARB 2018 dataset (ANL 2021, NREL 2021), which is especially important for high speed applications like long-haul trucks, for which there is limited data.

**FIGURE 2.** Energy efficiency ratio (EER) of electric trucks compared to diesel trucks




*Real-world and test-lab data provided by CARB (dark blue circles) plus more recent simulations by national laboratories (light blue squares) show that electric trucks are significantly more efficient than their diesel equivalent, at any speed. Fitting the data on a log-log plot finds a strong correlation which can then be used to interpolate to different duty cycles (black line, with dotted lines representing 95-percent confidence intervals). CARB's original fit (green line) is shown for reference.*

Figure 2 shows that the new simulation data is largely consistent with CARB's dataset. We fit the data to a general exponential relationship with average duty cycle speed, consistent with CARB's formulation. While at the lowest speeds, our estimate is up to 36 percent more efficient than CARB's estimate, at high speeds we see a significant reduction compared to CARB's data. CARB's original formulation lies within our 95 percent confidence bars, and for the duty cycles considered in this analysis, the average speeds are in the realm where our estimate of the EER is equal to or below that of CARB, making our analysis more conservative.

There is little systematic data available on the efficiency of electric trucks, though it is still worth comparing our assumptions to what data is available. There are a number of analyses looking at the opportunity for electric trucks in the long-haul sector which can help provide one test of the reasonableness of our electric truck assumptions. Pulling the data from the sources cited in a recent literature review (ICCT 2021), we find that CARB's data is at the upper maximum in EER, with the data indicating an average EER = 1.95-2.24, quite consistent with our fit at high speeds (1.6-2.7).

A comparison of the derived BEV efficiencies for the vehicles of interest and available real world data affirms this methodology (Table 5). Fleet demonstrations conducted by the North American Council for Freight Efficiency (NACFE) find that Class 8 diesel tractors can achieve at least 8.0 mpg, with a subset achieving as high as 8.7 mpg (NACFE 2019). A recent analysis of fleets running electric trucks showed an average efficiency of about 2 kWh/mi (NACFE 2022). Similarly, NREL data on efficiency from transit buses, school buses, and delivery trucks identify similar efficiencies of electric trucks in those operations. In fact, transit buses are the only application where our modeling identified a more efficient electric truck, but that data is based on a particularly demanding bus route, and the EER is actually much greater than assumed by this modeling.

Fuel-cell electric vehicles (FCEVs) will have the same efficiency advantages of BEVs, since they, too, are propelled by an electric drivetrain—it is the source of their electricity that drives disparities. For the efficiency of FCEVs, we use the vehicle-level efficiency of the BEV (i.e., excluding charger-related losses) and assume a fuel cell efficiency of 60 percent based on data from light-duty FCEVs (Kurts et al. 2019).

**TABLE 5.** Electric truck efficiency for each vehicle class, compared to real-world data (where available)

| Vehicle Type | Simulated Data | | | Real-world Data | | |
|---|---|---|---|---|---|---|
| | Diesel [mpg] | Electric [kWh/mi] | EER | Diesel [mpg] | Electric [kWh/mi] | EER |
| Delivery Van | 10.1 | 1.2 | 3.2 | | | |
| Delivery Truck | 7.1 | 1.7 | 3.2 | 7.6 | 1.4 | 3.6 |
| School Bus | 5.5 | 1.5 | 4.5 | 7 | 1.4 | 4.0 |
| Refuse Truck | 3.2 | 2.6 | 4.6 | | | |
| Tractor (Drayage) | 4.9 | 1.8 | 4.4 | | | |
| Tractor (Regional) | 6.4 | 2.4 | 2.5 | 8.0 | 2 | 2.4 |
| Tractor (Line-Haul) | 6.9 | 2.3 | 2.4 | | | |
| Transit Bus | 4.4 | 2.0 | 4.3 | 2.1* | 2.2* | 7.5* |

*On an energy basis, electric trucks can be more than 4 times as efficient as their diesel counterparts, particularly on the most intense duty cycles. Our modeling is consistent with the limited data on real-world applications—in fact, if anything our assumption about the energy efficiency (kWh per mile) of these trucks undersells the performance of electric trucks.*

*Note: Transit bus data is based on diesel equivalency of compressed natural gas buses run on the same routes. EER and energy efficiency includes an assumption of a 90 percent charger efficiency.

SOURCES: NREL 2015 (delivery truck), NREL 2017 (school bus), NREL 2021 (transit bus), NACFE 2019 and NACFE 2022.

## Smog-forming and Particulate Pollution

Despite the advent of diesel particulate filters, particulate emissions (PM) from trucks remain a critical public health issue. PM is often denoted by the size of the pollutant, either $PM_{2.5}$ or $PM_{10}$, for particles less than 2.5 or 10 μm in diameter, respectively. In addition to emissions related to combustion engines, PM from brake and tire wear represent a substantial source of PM emissions from all trucks.

There is limited available data on the tire and brake wear of electric vehicles, and what little study has been conducted is almost exclusively on light-duty passenger vehicles (see this for a review). Electric trucks are given a 4,000-pound allowance for gross vehicle weight rating, meaning that loaded they could weigh as much as 4,000 pounds more than their diesel equivalent, which would thus increase wear associated with tires. However, 4,000 pounds represents a small share of the total weight of a heavy-duty vehicle, and tire wear should be proportional to weight. Additionally, electric trucks can recoup energy through regenerative braking, which also has the benefit of reducing brake wear, an offsetting effect. These competing effects likely mitigate much of the potential difference in PM emissions from the two types of vehicles, and with limited data available to the contrary, this analysis assumes that PM emissions from brake and tirewear is assumed to be equivalent for all types of heavy-duty truck. While there is no difference in these emissions between the trucks, the health impacts of these emissions are factored into the analysis as a share of the total health impacts from the trucks.

Smog is formed from the reaction of nitrogen oxides ($NO_X$) or sulfur oxides (most commonly $SO_2$) with volatile organic compounds (VOCs) in the presence of sunlight. All three of these pollutants can be released from diesel-powered trucks, though low-sulfur diesel fuel has substantially reduced the amount of $SO_2$ typically emitted in diesel exhaust.

All four pollutants mentioned above (PM, $NO_X$, SO2, and VOCs) can be emitted from electric power plants as well as from the processes to obtain and refine fuel for both the transportation and power sectors.

Unlike light-duty vehicles, tailpipe emission standards have not historically been regulated at the vehicle level but rather the engine. This leads to standards that are based on lab tests of an engine on a dynamometer, rather than a tailpipe test. There are three such standards governing diesel vehicles concerned in this study. The way in which these engine standards translate into real-world emissions is complicated by a number of factors, which are discussed below.

Because the emissions controls may be improperly maintained outside of the warranty period, we use the same process as the EPA MOVES3 model to account for changes in emissions in $PM_{2.5}$ and $NO_X$ over a vehicle's lifetime related to mal-maintenance and tampering. This is then used to assess an average g/mi value for the usable lifetime. In this analysis, the usable lifetime is defined by B10 data for Class 4-8 vehicles, defined as the point at which 10 percent of the fleet must be rebuilt (CARB 2017). This is a conservative representation of the emissions impact of trucks, as the median engine (B50) can exceed this lifetime by as much as 50 percent according to that same dataset. Furthermore, it is an averaging process weighted towards the period under which a manufacturer is responsible for ensuring emissions controls are operational, though it still exceeds the full useful life and warranty periods of all standards considered.

### *Federal Standards for Model Years 2010-2026*

In 2001, EPA set emissions standards for heavy-duty trucks which were anticipated to require selective catalytic reduction (SCR) of engine emissions to reduce $NO_X$ and diesel particulate filters (DPFs) to reduce PM. Due to flexibilities in the final rule, these standards did not fully phase in until 2010. These standards require an average achieved standards of 0.20 g $NO_X$/bhp-hr, as measured on the FTP cycle, over the full useful lifetime mileage of the vehicle up to 435,000 miles for Class 8 trucks.

There is a large volume of evidence that exists on the effectiveness of this rule, which shows that in the real-world these engines emit far more $NO_X$ than intended by the rule. This is primarily related to shortcomings in the in-use requirements on manufacturers. A number of exceptions in the in-use requirements (which fall under what is known as a "not to exceed" (NTE) limit) mean that diesel emissions controls on these trucks operate suboptimally in a wide range of behavior which are not regulated under the in-use requirements. Essentially, these engines perform relatively well on the narrow range tested, but extremely poorly on the more than 90 percent of operating conditions not covered by those test procedures. As a result, these trucks can emit more than 7 times the required $NO_X$ standard under low-speed operation according to official data submitted by manufacturers as part of the in-use testing program (ICCT 2019).

To translate that data into real-world operation, we utilize the MOVES3 emissions rates for operating modes, and use the data from the vehicle test cycles to determine those operating modes (TABLE 1). The on-road $NO_X$ emissions are then converted into a g/mile. The NREL test cycles provide engine power data, allowing for easy determination of operating mode for MOVES3 categorization. For the refuse truck and school bus data, for which exists only speed trace information, kinetic energy during acceleration is used as a surrogate for power, with MOVES3 average accessory power used to represent engine utilization for non-tractive power.

While real-world $NO_X$ emissions fell well short of the anticipated reductions for 2010 and beyond, DPFs have proved more effective than originally anticipated. The MOVES3 model used by EPA to model real-world emissions impacts included an update to $PM_{2.5}$ emissions rates based on the same recent heavy-duty in-use testing (HDIUT) data with which the $NO_X$ emissions were updated (Figure 2-26, EPA-420-R-22-031). This data was summarized for a nationally representative duty cycle for each vehicle class (Classes 2b-3, 4-5, 6-7, 8, and bus). To account for differences in duty cycle, we adjust to reflect the differences in average $PM_{2.5}$ emissions for each speed bin based on a truck's given duty cycle, including idle, to come up with a g/mile number. This was done for both natural gas and diesel vehicles.

Quantities of VOCs are determined as a share of the MOVES3 hydrocarbon (HC) emissions based on speciation data (EPA 2022a). For diesel vehicles with aftertreatment systems, VOCs represent 59.83 percent of the total HC emissions. For natural gas vehicles, VOCs are much higher, though the vast majority of HC emissions stem from methane (EPA 2022b).

While ultra-low-sulfur diesel (ULSD) fuel has substantially reduced on-road emissions of $SO_2$, the direct emissions are considered as a ratio of the fuel based on the relative sulfur content. This analysis uses the emissions factors from GREET, which itself is based on an average in-use percentage of 11 ppm sulfur content, by weight, consistent with EPA's analysis of the ULSD requirements (EPA-420-R-04-007).

### *State Standards for Model Years 2024+*

Because the 2010 standards were so woefully inadequate, the State of California pursued a comprehensive rule governing heavy-duty trucks seeking not just to adjust the standards but also the test procedures, warranties, and full useful life requirement of these trucks to better ensure that the rule result in real-world emissions reductions from heavy-duty vehicles.

The Heavy-Duty Engine and Vehicle Omnibus Regulation for 2024 and Subsequent Model Years ("Omnibus") was finalized in 2020 by the California Air Resources Board and has since been adopted or is in the process of being adopted by a number of other states. The rule roughly set a 90 percent reduction in $NO_X$ emissions from heavy-duty vehicles, nearly doubled the useful life period of heavy-duty engines, dramatically extended the warranty requirements, expanded and strengthened in-use testing requirements, and introduced a new test cycle (the low load cycle, LLC) meant to capture low-load operation where, under the 2010 standards, modern emissions controls were operating suboptimally.

The Omnibus requirements are phased in under multiple steps, with the final step occurring in 2031, meaning that diesel trucks sold in a state adopting the Omnibus in 2035 will have to meet, on average, the most stringent requirements of the rule.

The real-world requirements of the rule reflect a completely redesigned in-use requirement to replace the ineffective NTE protocol. Under this new program, a truck's duty cycle is divided into overlapping, 300-second bins in what is known as a "moving average window" (MAW) approach. Depending upon the average $CO_2$ emissions from the engine within a bin, the $NO_X$ emissions are compared to a given engine requirement based on different lab test cycles and an in-use factor. Here $CO_2$ is used as a surrogate for power in assigning the comparison, either to Bin 1 (for normalized $CO_2$ rate less than or equal to 6 percent), Bin 2 (greater than 6 percent normalized $CO_2$ but less than or equal to 20 percent), or Bin 3 (greater than 20 percent).

The Bin 1 standard is based on the Clean Idle requirement of a given year, since it corresponds to operation comparable to idling and low-power of the low-load cycle. The Bin 2 standard is based on CARB's requirements for the LLC, multiplied by a conformity factor (2.0 for 2027-2029, 1.5 for all other years). The Bin 3 standard is based on the SET/FTP standard, multiplied by the same conformity factor.

For $PM_{2.5}$ emissions, the Omnibus standards are meant to act as a backstop—current vehicles meet the in-use requirements for $PM_{2.5}$, and therefore it is assumed that vehicles meeting this standard will perform equivalently to today's vehicles. The same assumption is made for HCs, for which CARB has not set an additional standard for diesel vehicles.

As in the case of the 2010+ standards, malmaintenance and tampering were considered. However, because the difference between engine-out and tailpipe emissions is so much greater, so is the impact of any tampering. This analysis relies upon new MOVES3 factors for tampering developed as part of EPA's 2027 $NO_X$ rulemaking (described below), adjusted for the more stringent in-use requirements of CARB's program for $NO_X$. For all other pollutants, malmaintenance and tampering emissions are the same as MOVES3.

### *Federal Standards for Model Years 2027+*

In December 2022, EPA finalized its own $NO_X$ standards for model years 2027 and beyond. These standards are less stringent than the state standards above but largely follow a similar structure. One major difference is that rather than a 3-bin MAW approach, EPA's standards are based on just 2 bins, Bin 1 (for normalized $CO_2$ rate less than or equal to 6 percent) and Bin 2 (greater than 6 percent normalized $CO_2$). However, the process to generate emissions for each truck type are largely identical, excepting for different numerical values of the standards, warranty periods, and required useful life periods.

The Bin 1 standard (10 g/hr) is based on the optional Clean Idle standard, since it corresponds to operation comparable to idling and low-power of the low-load cycle. The Bin 2 standard (58 mg/hp-hr for LHD, 73 mg/hp-hr for MHD and HHD) is based on a 25/75 percent mixture of the LLC (50 mg/hp-hr) and FTP (35 mg/hp-hr) standards, respectively, along with a conformity factor of 1.5 and, for MHD and HHD engines an additional "interim" adjustment of 15 mg/hp-hr.

On top of this, the Bin 1 and Bin 2 standards are further adjusted with respect to the work-day temperature of the vehicle being tested. This temperature adjustment factor enables manufacturers to scale the in-use requirement for each bin linearly within a given temperature window (5°C < $T$ < 25°C), below which data is exempted and above which the factor is unity. This scalar can be as much as a 60 percent increase in emissions for MHD and HHD engines and as much as 76 percent for LHD engines (Table III-18, 88 FR 4349).

In its own analysis, EPA assumed that in virtually all operating conditions, the off-cycle standards would represent the binding constraint on engine emissions (RIA p. 238). However, in assessing the rule's impact, the Agency assumed a more binding idling standard (5 g/hr instead of 10 g/hr), ignored the interim adjustment for MHD engines (15 mg/hp-hr), ignored the additional allowance for measurement accuracy (5 mg/hp-hr), and ignored the temperature adjustment altogether. This means that EPA's own analysis assumes that emissions in the real-world will be much lower than is actually required by the finalized standards.

### The implied effect of temperature on emissions

To assess the average impact this temperature adjustment has on real-world emissions, it is necessary to consider the temperature profile experienced by a truck through the workday, since this determines the magnitude of the additional allowance granted to manufacturers. Below is detailed an average temperature profile experienced by freight traffic throughout the United States. First, hourly traffic flow for a given truck type is assessed. Then, this hourly traffic volume is correlated to an experienced temperature. Finally, this data is then weighted by the freight volume of a given geography to provide an expected national profile for each truck type. This is then used to assess the magnitude of the additional allowance for different vehicle types. Those vehicle types (from the Federal Highway Administration, FHWA) are then applied to those studied in this analysis (Table 6).

**Hourly truck traffic**

It is possible to look at average truck traffic to obtain a national profile for a given vehicle class. A report requested by FHWA details hourly truck traffic for different vehicle types by hour over the course of the day, by month compared to an annual average, and for different road types (Hallenbeck et al. 1997). The report identifies different usage profiles, noting differences in hourly travel profiles for vehicles like long-haul trucks, which include a non-trivial amount of overnight travel, as compared to local delivery vans or buses, which operate on a business hours basis (Figure 3). This travel pattern data is used to create a 365-day × 24-hour data set for each truck class defined by FWHA (Table 7), based on the traffic volumes for each road type (Table 8).

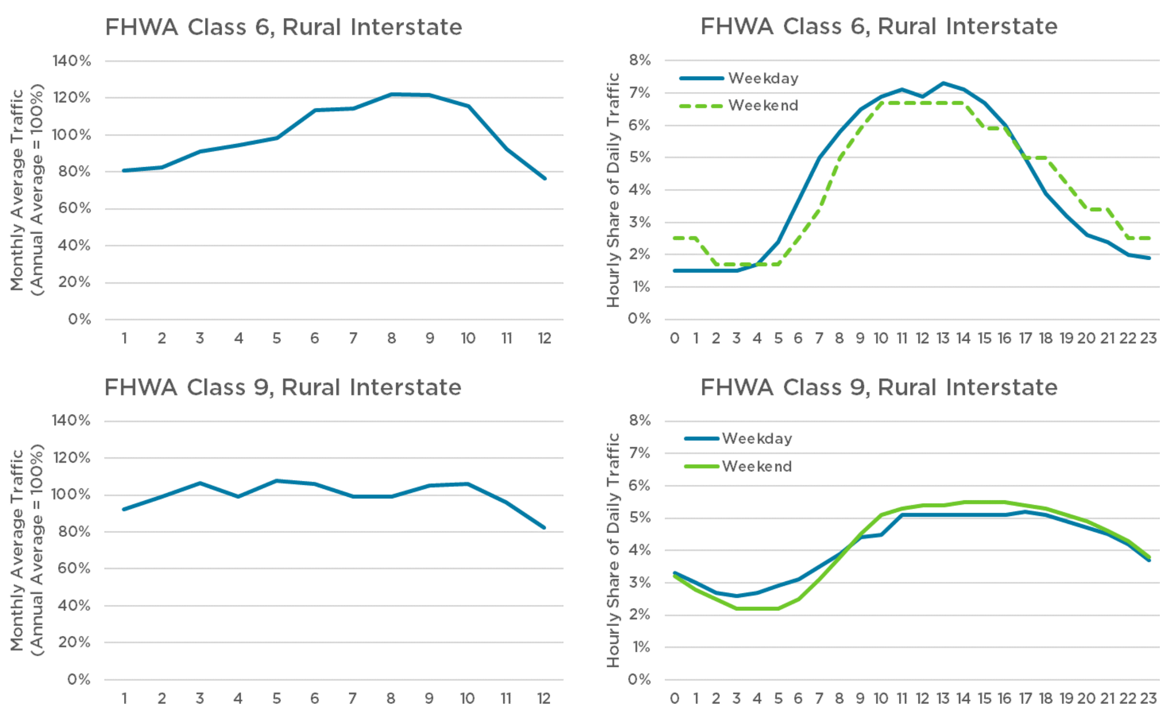
**TABLE 6.** Heavy-duty vehicle types assigned to Federal Highway Vehicle class (Hallenbeck et al. 1997)

| Vehicle Class | Vehicle Type | Federal Highway Vehicle Class |
|---|---|---|
| Class 4 | Delivery Van | 2-axle 6-tire single-unit truck (Class 5) |
| Class 6 | Delivery Truck | 2-axle 6-tire single-unit truck (Class 5) |
| Class 6 | School Bus | Buses (Class 4) |
| Class 8 | Refuse Truck | 3-axle 6-tire single-unit truck (Class 6) |
| Class 8 | Tractor (Drayage) | 5-axle combination truck (Class 9) |
| Class 8 | Tractor (Regional) | 5-axle combination truck (Class 9) |
| Class 8 | Tractor (Line-Haul) | 5-axle combination truck (Class 9) |
| Class 8 | Transit Bus | Buses (Class 4) |

### Temperature profile for a truck in a given geography

The National Ocean and Atmospheric Administration (NOAA) has collected hourly temperature data from sites around the country for decades. This data has been used to compile “climate normal” temperature and climate information to represent the average weather a location would be expected to see, for comparison to current and future weather conditions (NOAA 2021).

**FIGURE 3.** Traffic volume data for Class 6 and Class 9 trucks by month and day, on rural interstates




*Traffic flow data is available across a broad range of trucks and road types, illustrating different hourly and seasonal behavior. For example, FHWA Class 6 straight trucks observe a clear workday operation and more peaked seasonal behavior than FHWA Class 9 tractor-trailers, which show more homogeneity at both the hourly and monthly level.*

**TABLE 7.** Federal Highway Administration vehicle classification

| Federal Highway Vehicle Class | Vehicle Description |
|---|---|
| Class 1 | Motorcycles |
| Class 2 | Passenger cars |
| Class 3 | Other 2-axle, 4-tire single-unit vehicles |
| Class 4 | Buses |
| Class 5 | 2-axle, 6-tire single-unit trucks |
| Class 6 | 3-axle, 6-tire single-unit trucks |
| Class 7 | 4+ axle single-unit trucks |
| Class 8 | 4 or less axle combination trucks |
| Class 9 | 5-axle combination trucks |
| Class 10 | 6+ axle combination trucks |
| Class 11 | 5-axle multi-trailer trucks |
| Class 12 | 6-axle multi-trailer trucks |
| Class 13 | 7+ axle multi-trailer trucks |

*The heavy-duty engines covered by the 2027+ EPA $NO_X$ program are found in Class 4-13 trucks.*

**TABLE 8.** Functional classification of roadways used by the Federal Highway Administration

| Federal Highway Road Class | Roadway Description |
|---|---|
| Class 1 | Rural Interstate |
| Class 2 | Rural Principle Arterial |
| Class 6 | Rural Minor Arterial |
| Class 7 | Rural Major Collector |
| Class 8 | Rural Minor Collector |
| Class 11 | Urban Interstate |
| Class 12 | Urban Other Freeways and Expressways |
| Class 14 | Urban Principle Arterial |
| Class 16 | Urban Minor Arterial |
| Class 17 | Urban Collector |

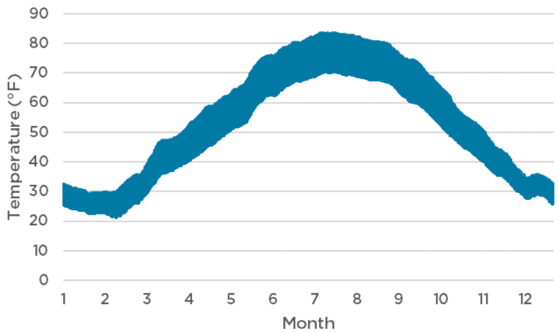
*Traffic count data is available my functional road class. Hourly and monthly traffic flow data on local roadways was not available for this analysis but remains a small share of the total traffic flow (less than 14 percent in 2020; FHWA 2021).*

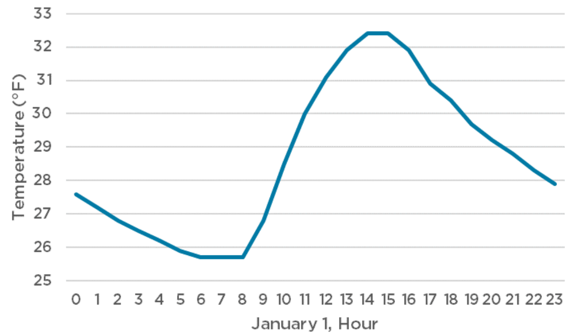
This data is available on a site-by-site basis (NOAA n.d.). Thus, for a given region, it is possible to obtain a typical temperature profile for the year. With the hourly travel data already collected for each truck class, it is thus possible to estimate the typical temperature experienced throughout the work day (Figure 4).

### Obtaining a national average temperature profile

Because the hourly temperature data for a region can now be applied to the hourly truck traffic profile for each type of truck over the course of the year, the question now is how to consider the different geographies around the country.

**FIGURE 4.** Climate normal temperature at Chicago-Midway Airport




*Climate normal temperature shows clear seasonal behavior over the year, but the hourly result shows even a wide range of temperatures over the course of a single day. This variance causes the wide band present in the annual data.*

The Freight Analysis Framework (FAF) from the FHWA provides a way to weight truck traffic around the country. The FAF divides the country into 132 freight regions. Data is available on value and ton-mileage of freight by different modes between those regions, including via truck. Most of those regions are defined by cities, which correlates well to NOAA climate monitoring sites. However, for the remainder (which take the form “Rest of [State]”), a temperature monitoring site was identified by looking at the daily truck volume (Figure 5) and assigning the site with the highest volume flow not already covered by a freight area (e.g., “Rest of Virginia” was assigned to Roanoke, VA, because the Washington, DC; Richmond, VA; and Virginia Beach-Norfolk, VA metropolitan areas were already covered).

Having correlated freight areas with temperature data, now it becomes a question on how to weight those different freight areas. This analysis averaged the freight ton-mileage for which a given site is an origin and for which the freight area is a destination. The top ten freight areas represent just over one-quarter of the traffic flow and are shown in Table 9, along with the location of their representative climate monitor and freight share.

These regions of the country span a wide assortment of climate behavior, and (as is indicated in Figure 5) if anything this methodology weights typical workday operation away from the coldest regions of the United States, where one might expect the temperature adjustment to make the biggest impact given the relatively high temperature below which it affects manufacturers’ obligations.

Combining this freight data with the traffic volume and NOAA temperature data allows us to calculate a representative national profile for any given truck type—an example of line-haul tractor-trailers (FHWA Class 9) is shown in Figure 6. In this example, just over 17 percent of operation would be excluded from the in-use program, and just over 19 percent would be required to meet the in-use protocol with no temperature adjustment. This means nearly two-thirds of the expected operation of an average truck would received an additional adjustment related to temperature.

**FIGURE 5.** Estimated average daily volumes for trucks on the National Highway System. 2017, according to the Freight Analysis Framework (FHWA 2018)

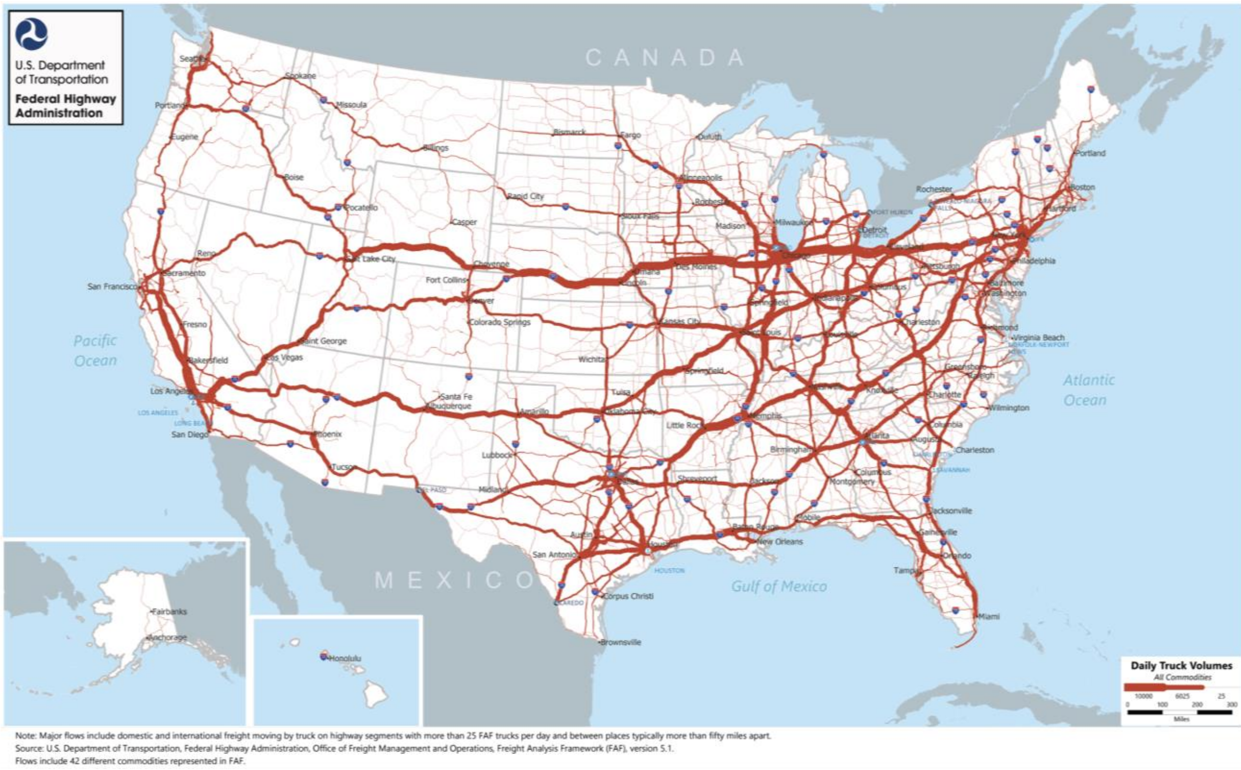
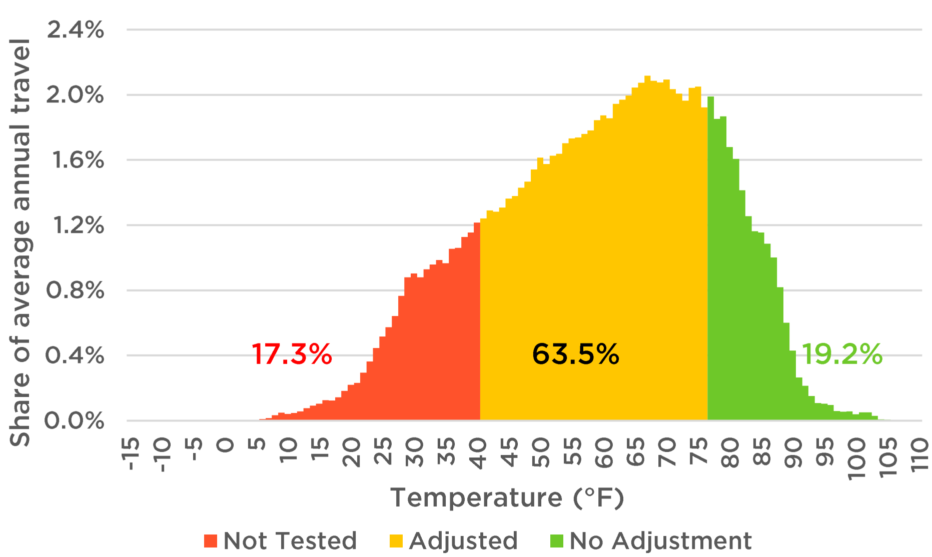



**FIGURE 6.** Freight-weighted temperature profile for line-haul tractor-trailers (FHWA Class 9).




*Nearly two-thirds of freight travel occurs at a temperature under which the in-use standard is relaxed, and more than 17 percent of freight travel occurs at a temperature for which in-use data is exempted. This leads to a substantially relaxed in-use requirement for manufacturers under the federal $NO_X$ standards for model years 2027 and later.*

**TABLE 9.** Freight areas with the highest average combined ton-mileage of origin and destination

| Freight Area | Representative City | State | Share |
|---|---|---|---|
| Rest of TX | Amarillo | TX | 5.0% |
| Los Angeles CA | Los Angeles | CA | 4.3% |
| Iowa | Des Moines | IA | 3.0% |
| Dallas-Fort Worth TX-OK (TX Part) | Dallas-Ft. Worth | TX | 2.8% |
| Houston TX | Houston | TX | 2.6% |
| Chicago IL-IN-WI (IL Part) | Chicago | IL | 2.3% |
| Rest of WI | Madison | WI | 2.3% |
| Rest of IL | Springfield | IL | 2.3% |
| San Francisco CA | San Francisco | CA | 1.9% |
| Rest of MN | Duluth | MN | 1.8% |

*The highest average freight ton-mileage is found at ports of entry and/or through stops on freight corridors.*

**Expected adjustment to in-use off-cycle bins**

Though much of the temperatures experienced by a truck are very moderate, the impact of this large temperature coverage leads to a rather substantial expected adjustment for trucks. Manufacturers submitted the data underpinning this adjustment factor, and as with any flexibility it should be assumed that manufacturers will take full advantage of this in designing and packaging emissions controls such that there will be increased emissions at different temperatures. Since manufacturers have flexibility on determining which vehicles are measured against the in-use requirements, it's likely this adjustment factor will even be selected for explicitly in the design phase.

To calculate the impact of the temperature adjustment, the temperature adjustment for the idle and in-use bin was applied, and temperatures below 5°C were ignored. The freight-weighted adjusted bins are shown in Table 10. It should be noted that in-use emissions will be even higher due to the exempted data below 5°C, where there is absolutely no guarantee that emissions controls are operating effectively.

These adjusted off-cycle bins represent a significant increase which EPA did not consider in its analysis of the emissions from engines certified to the final $NO_X$ standards, with idle emissions in particular more than double those assumed in the regulatory impact analysis. While we have not attempted to convert these substantial increases into a fleet-wide estimate of benefits, it is clearly significant. And with manufacturers getting to preferentially select the trucks tested under this program, it could be manipulated even further to erode the efficacy of the in-use requirements.

There is no temperature adjustment for any pollutants other than $NO_X$. For $PM_{2.5}$ and HCs, current vehicles already achieve the required targets, so it is assumed that vehicles meeting the EPA standards will achieve the levels of performance of today's vehicles. MOVES3 data is then used to estimate the emissions for each vehicle category.

Lifetime-weighted pollution rates are calculated as in the other classes, considering a multiplicative adjustment for effectiveness as calculated by EPA in support of the 2027 $NO_X$ rule (Section 5.2.2.1.2, EPA 420-R-22-035). The malmaintenance factors were again adjusted relative to the values used in the rulemaking to reflect differences between the modeled and finalized standards, consistent with the approach taken in assessing the malmaintenance impact on the CARB standards.

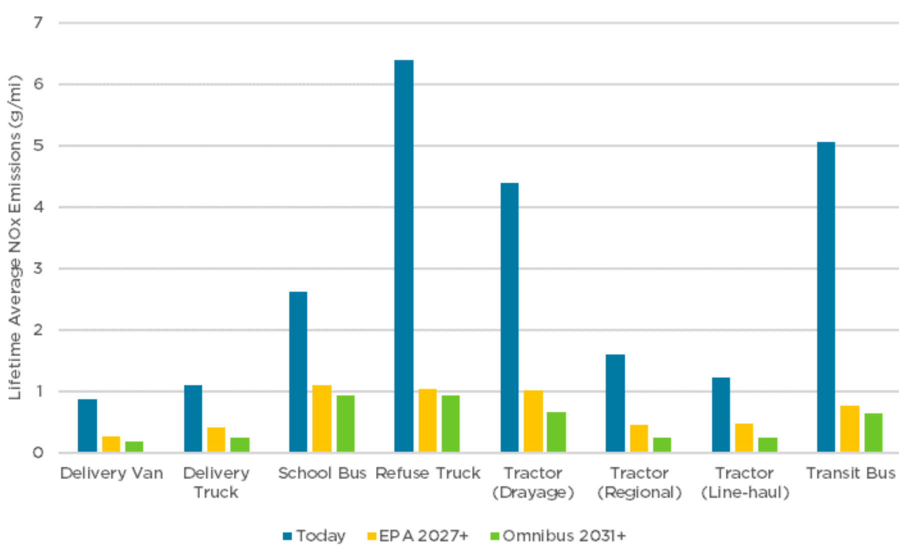
**TABLE 10.** Comparison of temperature adjusted off-cycle requirements for FHWA vehicle classes

| FHWA Class | Adjusted Bin 1 | Adjusted Bin 2** | Share Not Tested | Share Adjusted | Share No Adjustment |
|---|---|---|---|---|---|
| 4 | 11.8 | 74 | 18.1% | 62.6% | 19.4% |
| 5 | 11.6 | 72 | 15.4% | 61.6% | 22.9% |
| 6 | 11.5 | 71 | 14.1% | 61.3% | 24.7% |
| 7 | 11.4 | 70 | 11.6% | 60.3% | 28.1% |
| 8 | 11.5 | 72 | 14.4% | 61.0% | 24.5% |
| 9 | 11.8 | 73 | 17.3% | 63.5% | 19.2% |
| 10 | 11.7 | 73 | 17.1% | 64.0% | 18.9% |
| 11 | 11.9 | 75 | 19.0% | 65.6% | 15.4% |
| 12 | 11.9 | 75 | 19.8% | 64.5% | 15.7% |
| 13 | 11.9 | 75 | 18.7% | 66.5% | 14.8% |

*Compared to a nominal Bin 1 standard of 10 g/hr and a nominal Bin 2 standard of 58 mg/hp-hr, the typical truck would be expected an additional allowance of 14-19 percent idle emissions and 21-30 percent additional in-use emissions.*

**NOTE: The adjusted Bin 2 values do not include the 15 mg/hp-hr interim allowance for MHD and HHD engines nor the additional 5 mg/hp-hr allowance for measurement accuracy (40 CFR § 1036.420), which our analysis did not include.

**FIGURE 7.** Comparison of lifetime average real-world $NO_X$ emissions for different vehicle types




*A comparison of the impacts of the federal and state $NO_X$ standards shows a substantial difference in emissions, with the federal program leading to average emissions about 50 percent higher for the selected vehicle types, with line-haul tractors showing the greatest disparity (85 percent).*

### *Comparison of $NO_X$ real-world $NO_X$ emissions*

To illustrate the impact of $NO_X$ emissions standards on real-world tailpipe emissions, lifetime average emissions are compared across vehicle types in Figure 7 to reflect not just emissions when the vehicle is new but averaged over the expected lifetime to account for in-use factors, degradation related to expired warranty and malmaintenance, etc. As noted previously, this lifetime is determined by the mileage at which 90 percent of the fleet would be rebuilt.

## Electricity Grid Emissions

While electric trucks have zero tailpipe emissions, the electricity associated with charging the batteries powering electric trucks certainly has associated global warming, smog-forming, and particulate emissions. At the same time, these emissions are getting better over time, and this is expected to continue (UCS 2022, Figure 4). Therefore, in order to better characterize the impacts of these vehicles, we consider the current state of the grid as well as the grid as it is likely to be in the future when these vehicles are a significant share of on-road heavy-duty trucks (2035).

### Today's grid

The most current EPA data on grid generation and emission rates is used to represent the current grid data (eGRID2021). This data is disaggregated into subregions of the North American Electric Reliability Corporation (NERC) which reasonably approximate the grid mix of electricity used by a household within the region, owing to the overall complexity of the supply and distribution of electricity.

eGRID provides direct emissions of nitrogen oxides ($NO_X$), sulfur dioxide ($SO_2$), methane ($CH_4$), nitrous oxide ($N_2O$), and carbon dioxide ($CO_2$). In order to incorporate upstream emissions, as well as the missing particulate emissions, the source generation data from eGRID is input into GREET.

### Future grid

To characterize emissions from the future grid, we rely predominantly on analysis from the National Renewable Energy Laboratory (NREL). As part of its Cambium project, NREL utilizes a least-cost structural model to project future grid elements together with a tool that models hourly grid operation to assess grid characteristics under different future policy scenarios (Gagnon et al. 2021).

The NREL analysis is able to generate a long-run marginal emissions rate, which is defined as the emissions induced or avoided by a long-term change in electricity demand, such as what would be induced by an increasing share of electric vehicles. While recent analysis of the long-run marginal emissions rate shows that it can more accurately predicts emissions impacts related to operational responses to changes in electricity demand than either the short-run marginal emissions rate or the average emissions rate (Gagnon and Cole 2022), the marginal production by source is not provided with the Cambium model data, which means it is not possible to establish non-greenhouse gas long-term marginal emissions rates. Additionally, eGRID2021 provides average emissions data, so using average emissions rates provides a clearer "apples to apples" comparison between current and future grid emissions. As a result, this analysis uses the average emissions rate for greenhouse gas emissions.

There are a number of potential future grid conditions based on today's policy landscape. UCS has conducted its own economywide decarbonization analysis, consistent with the science-based position to address climate change by achieving net-zero emissions by 2050 (UCS 2021). The Cambium scenario most consistent with this UCS modeling is a 95 percent reduction by 2035. For comparison, the Biden administration, which has also called for a net-zero emissions economy by 2050, has called for a 100-percent "carbon pollution-free" power sector by 2035 to help achieve these targets.

The Cambium analysis is provided in two-year increments—for simplicity, we have used a linear interpolation between the 2034 and 2036 datasets to obtain 2035 data for the average emissions rate as well as the share of generation. To assess non-greenhouse gas emissions, as well as upstream impacts for the grid, we apply source generation from the NREL Cambium analysis to GREET.

While the generation and emissions assessment (GEA) regions overlap significantly with the NERC regions, there are a few differences. The upstate New York (NYUP) and New York City/Westchester (NYCW) subregions are combined into a single balancing area (p127), and the Long Island (NYLI) subregion is not listed as a separate GEA region but only as its own balancing area (p128). Most importantly, however, the Cambium data is available only for the contiguous United States, so there is no data modeled for Alaska or Hawaii.

Hawaii has a 100 percent renewable portfolio standard (RPS) for 2045, along with interim targets. As such, Hawaiian utilities have to report on their progress in achieving those targets (Katsura 2022, Rockwell 2022). In addition to these reports, the utilities include planned projects not yet online, including projects already approved by regulators (Hawaiian Electric 2022, Kauai Island Utility Cooperative 2022). Most of these planned projects are utility-scale solar, though the West Kauai Energy Project includes pumped hydropower and is expected to provide over 20 percent of Kauai's power renewably in the coming years. In addition to these approved projects, there are additional planned "Stage 3" required renewable proposals that will substantially increase the renewables on the grid before 2035 beyond what is already confirmed over the next five years, including specifically for firm power (State of Hawaii PUC 2023). These and the existing plans support the utilities' planned shutdown of fossil fuel power plants, which we anticipate will continue (HECO 2022). Some of this firm power is driven by a significant growth in battery-energy storage systems (BESS), which can also increase the available capacity of existing variable renewable resources (GE Energy Consulting 2017). Based on the amount of BESS already planned and the modeling prepared for the Hawaii Natural Energy Institute, we project an increased utilization of just under 15 percent for resources already part of Oahu's grid.

We estimate that, compared to RPS targets of 40 percent in 2030 and 70 percent in 2040, the Hawaiian Electric Company will achieve 82 percent in 2035 (up from 32 percent today) and the Kauai Island Utility Cooperative 93 percent in 2035 (up from 69.5 percent today). While the subgrid supporting the other islands (HIMS) is projected to virtually eliminate its remaining petroleum power in this timeframe as a result of all these commitments, nearly one quarter of power for Oahu (HIOA) is anticipated to continue being supplied by petroleum power plants in 2035 under these assumptions.

The projected grid data was then applied to GREET. To calculate direct emissions from this grid mix, we scale back as needed eGRID2021 data to accommodate the various renewable projects, with an exception for the closure of Hawaii's last coal plant in Oahu (Shao 2022). Unlike eGRID2021, consumer-side solar was included in our assessment of the final GREET mix for both sales and production because it represents a substantial share of both the total generation (19 percent for HIMS and 28 percent for HIOA) and contribution towards achieving the RPS targets, and its exclusion in eGRID is based primarily on data collection limitations at the national level. To calculate the emissions from this grid mix, we use GREET, as above.

Unlike Hawaii, Alaska does not have any RPS requirements. However, NREL recently conducted a study on achieving an 80 percent RPS in the state's "railbelt", which represents 75 percent of the state's electric load (Denholm et al. 2022). This essentially corresponds to the eGRID subregion labeled ASCC Alaska Grid (AKGD). As part of its analysis of the railbelt, NREL considered a number of different scenarios. Because the RPS is identical in all scenarios, there is little difference in greenhouse gas emissions in any of the individual scenarios, though the fossil source generation does differ in each scenario. Because of planned expansion of both wind and hydroelectric generation, our analysis uses Scenario 2 as a reasonable estimate of a future, cleaner railbelt grid (DeMarban 2022, Kleinschmidt Associates 2022). In addition to the railbelt, Alaska is serviced by a large number of microgrids due to the state's unique environment, size, and sparse population. Hydroelectric power currently provides nearly two-thirds of the generation needed in the rest of the state, though this is currently backed up with diesel generators in order to provide continuous power, and many areas are serviced solely by diesel generators. Battery backup and wind power have enabled some of these microgrids to substantially reduce reliance on diesel to date, and future renewable energy projects are planned in a number of areas to reduce the high electricity costs of diesel dependency (EIA 2022). For simplicity, it was assumed that diesel fuel generation was replaced with renewable sources to achieve the same 80 percent RPS as AKGD, which leads to shares that are virtually identical to Scenario 1 in the NREL analysis for the ASCC Miscellaneous subregion (AKMS).

While the analyses for Alaska and Hawaii are less ambitious than the Cambium policy case, they both lead to substantial levels of greenhouse gas emissions reductions achievable in the timeframe of interest for this analysis of electric trucks. However, they do both leave a considerable share of remaining diesel/oil generation that reduces the public health benefits of electric trucks.

## Public Health Impacts

By shifting emissions from the on-road to electricity sector, not only do electric trucks change the amount of emissions of different pollutants, but they also shift the impacts of those emissions. For example, while 36 million people live within 3 miles of a power plant (EPA 2015), 72 million people are estimated to live within 200 meters of a freight route (88 FR 4324), a larger slice of the population despite it being a much narrower radius of proximity. However, in both cases, the populations are disproportionately communities of color and lower-income, a severe environmental justice issue which we do not further explore in this analysis.

### Contiguous United States

For the health impacts of VOCs, $NO_X$ and $SO_2$, in particular, location can matter significantly because the largest impact (as measured in monetized impacts) is related to the secondary formation of particulate matter from these pollutants, the dependence of which is related to complex, spatially dependent air quality modeling.

Because the location of the sources of pollution and the location of the affected populations vary so significantly between the electrical grid, freight traffic, and the upstream impacts from the fossil fuels used in both, this analysis attempts to consider location in its estimates of the health impacts from these very different emissions sources using EPA's Co-benefits Risk Assessment (COBRA) tool.

The COBRA tool uses a matrix to model changes in total concentration of $PM_{2.5}$, including via secondary formation from other pollutants. The impacts from these changes are then determined from health impact functions taken from the literature to estimate changes in premature mortality, heart attacks, etc. and reflect input assumptions on population. These can then further be converted into a monetary value.

A 2023 baseline is utilized—while this may not directly correspond to air quality changes, similar analyses of future years in BenMAP identified greater impact for the same ton of reduction in outer years, in terms of both incidence and monetary value, so if anything this is a conservative assumption (EPA 2023).

To reflect the difference in source of emissions, COBRA is used to determine per tonnage impacts for four different sector categories: 1) Highway Vehicles—Diesel—Heavy-duty, for direct emissions from trucks; 2) Fuel Combustion—Electric Utility, for grid emissions; 3) Petroleum and Related Industries—Petroleum Refineries and Related Industries, for upstream refinery emissions; and 4) Petroleum and Related Industries—Oil and Gas Production, to capture upstream emissions from fossil fuels. It should be noted that feedstock emissions from the electric grid include coal mining, which is not captured in #4; however, natural gas plants remain the larger share of feedstock emissions according to GREET's modeling, something that is especially true in the case of the future grid, and since this modeling exercise does not consider explicitly emissions from specific plants, this seems a reasonable compromise for simplicity.

In all cases, these factors are aggregated over the eGRID NERC subregions. Because COBRA data is given at the county level, we use eGRID to assign NERC subregion to the county level based first on the largest share of generation, and then using the area map for sources with no generation.[3] This means that impacts are proportional to the respective sources of such emissions in the subregion. For example, if one region's freight traffic travels more distant from population centers, on average, this will be reflected in a reduced impact factor. Or, if a region's emissions are dominated by a single power plant, that region's grid impacts will largely reflect an impact factor in line with that plant's outcomes.

By considering upstream health impacts from diesel fuel use in this way, we may not be accurately reflecting the real-world market outcomes. For example, the refinery level impacts from reducing diesel fuel use may largely result in benefits outside the subregion of interest. However, given that fuel refinery and distribution does generally have a strong regional component and the large size of the subregions, this assumption feels more reasonable than assuming a single national average impact.

To assess the health impacts, the changes in feedstock, fuel, and use emissions between the different categories of truck are considered and multiplied by their respective factors for all pollutants to assess the relative health benefit in a given subregion.

### Alaska and Hawaii

The COBRA model is underpinned by air quality modeling; however, such modeling excludes the states of Hawaii and Alaska in its analysis. Therefore, COBRA cannot be used to generate health impacts in the same way.

Despite a dispersed populace, Alaska has a significant air quality challenge, owing in large part to the temperature inversions in winter time, which exacerbate the increase in particulate matter from burning fossil fuels for heat and electricity (Schmale et al. 2018, Ye and Wang 2020). The health impacts in Alaska are thus likely to vary significantly from anywhere else in the United States.

[3] While this does create some imprecision or inaccuracy at the boundaries of some of the subregions, this affects a very small share of counties where there might be overlapping subregions, and the error would further be of second order even in that already small share, so this simplifying assumption should not have a meaningful effect on the results.

Similarly, Hawaii has its own unique air quality challenges owing to location and geology. In particular, volcanic smog ("vog") can be particularly hazardous, and while the island geography tends to reduce the formation of ozone because of trade winds, particularly in the summer (State of Hawaii 2020), weather patterns across the Pacific can bring ozone from the Eurasian continent to Hawaii (Lin et al. 2014). Additionally, the island geography limits the maximum distance between population centers and pollution sources, which can create significant environmental health and justice issues. This is particularly true for the large share of the state's population which lives in Honolulu, on Oahu, where vehicle emissions are one of the largest sources of pollution.

Given the lack of comprehensive data built on the air quality and populations of Alaska and Hawaii, but recognizing that secondary formation of $PM_{2.5}$ will still play a role in future health impacts related to the deployment of electric trucks in both states, this analysis uses national average health impact factors for $PM_{2.5}$, VOCs, $NO_X$, and $SO_2$ for the states of Alaska and Hawaii.

## Public Health Scores

While the aggregation of the health impacts of each type of truck provides an apples-to-apples comparison (for a given snapshot in time, under other assumptions regarding assessment of emissions), such information does not easily convey useful points of reference for understanding the relative harms of a technology over its lifetime. To better convey the relative public health harms of a given technology, we have devised a Public Health Score.

The most visible component of poor air quality is particulate matter emissions, which remain tragically high throughout numerous communities near freight corridors, and which can see huge spikes related to wildfires and other extreme events. Communities impacted by such pollution have developed a familiarity with the air quality index (AQI), a scale with associated health categories and colorization (Table 11).

AQI is based on the concentration of a given pollutant, but in a non-linear way (AQI is not directly proportional to concentration). We know that particulate matter is directly proportional to mortality,[4] so we have taken our mortality values and used them to generate a $PM_{2.5}$ equivalent value. While diesel truck pollution remains just one aspect affecting air quality, even in communities inundated with freight pollution, there is a clear understanding of the "unhealthy" levels of pollution driven by today's trucks. Therefore, we have benchmarked our public health scores relative to the impact of today's diesel vehicles in a given subregion, scaling the mortality values such that an effective concentration of $PM_{2.5}$ for today's diesel trucks representing 103 $\mu g/m^3$, a level corresponding to the middle of the "Unhealthy" range in the air quality index (AQI = 175). Because the health impacts of the different emissions sources from diesel trucks vary spatially (e.g., depending on the population near refineries vs. highways, reducing direct emissions will have a different effect on total health), public health scores are not

[4] Details of the scientific literature, including the "causal relationship" between short-term and long-term exposure to $PM_{2.5}$, can be found in U.S. EPA. Supplement to the 2019 Integrated Science Assessment for Particulate Matter (Final Report, 2022). EPA/635/R-22/028, 2022. The proportional relationships used in COBRA come from two signature studies, Krewski et. al. 2009 and Lepeule et al. (2012): Krewski, D., *et al*. 2009. "Extended follow-up and spatial analysis of the American Cancer Society study linking particulate air pollution and mortality," *Res. Rep. Health. Eff. Inst.* **140**, 5-136. https://pubmed.ncbi.nlm.nih.gov/19627030/; Lepeule, J., *et al*. 2012. "Chronic exposure to fine particles and mortality: an extended follow-up of the Harvard Six Cities study from 1974 to 2009," *Environ. Health Perspect.* **120** (7), 965-970. http://dx.doi.org/10.1289/ehp.1104660.

directly comparable to each other but are meant merely to reflect relative changes for different technologies. This is also why 2021 diesel truck scores are uniform but 2035 scores vary regionally.

While these “Public Health Scores” are correlated with air quality, they do not directly represent the AQI associated with pollution from trucks: 1) trucks are generally not the only component in a community’s air quality; 2) to the extent they are, that impact is dependent upon the relative volume of trucks in a given community; 3) generally, concentration of pollutants is dependent upon complex mixing of air and location relative to any pollutant source.

**TABLE 11.** Public health score, lifetime mortality, and relative impact compared to today’s diesel trucks

| | **Public Health Category** | **Category Score Range (Today’s Diesel = 175)** | **Difference in Mortality Compared to Today’s Diesel** |
|---|---|---|---|
| | Hazardous | 300 or higher | > 140% increase |
| | Very Unhealthy | 201-300 | 46% to 143% increase |
| | Unhealthy | 151-200 | 46% decrease to 46% increase |
| | Unhealthy for Sensitive Populations | 101-150 | 66% decrease to 46% decrease |
| | Moderate | 51-100 | 88% decrease to 66% decrease |
| | Good | 0-50 | 100% decrease to 88% decrease |