Quantifying the Impact of Transportation on Climate - Energy Analytics Dashboard

Preprint

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Quantifying the impact of transportation on climate - energy analytics dashboard

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Abstract

The investment decisions within the nation's transportation sector have traditionally been prioritized and measured against safety and travel efficiency goals. Increasingly, federal, state, and local policies are requiring consideration of energy use and emissions in the design of our transportation infrastructure. Yet the processes, analytics, and knowledge to include these new metrics into transportation decisions are lacking. Although targeted studies and before and after analysis are performed from time to time, no comprehensive real-time monitoring systems provide energy and emissions to the same level as congestion and safety. This paper describes work to address this gap—specifically, development and demonstration of the Transportation Energy Analytics Dashboard, or TEAD, to raise awareness of transportation energy and emission impacts to the same observability level as safety and mobility concerns.

Keywords: Sustainability, energy use, emissions

Introduction

Legacy transportation system investment and operational decisions are primarily based on safety and mobility considerations. While sustainability is also considered, it does not receive the same level of attention. Though sustainability tools such as the Environmental Protection Agency's Motor Vehicle Emission Simulator (MOVES) [1] provide valuable information on vehicular energy use and emissions, applying MOVES on a widespread and regular basis requires significant resources from highly trained professionals. Moreover, MOVES does not directly support real-time, traffic operations decisions.

Recognizing the opportunity to fill this much needed research gap, this project aimed to develop an online suite of transportation sustainability tools, named the Transportation Energy Analytics Dashboard (TEAD), to streamline the process of estimating energy use and emissions from roadway motor vehicles. These tools were designed to leverage data that transportation agencies regularly collect or have access to including vehicle probe data, traffic volume data, and vehicle registration data. The TEAD analysis tools were developed to estimate energy use, CO_2, NO_X, PM2.5, PM2.5 precursor for NO_X, and VOC emissions on individual road segments. These road segments are derived from probe vehicle data reporting segments called Traffic Message Channels (TMCs). Probe data supports the minute-by-minute estimation of energy use and emissions under the TEAD methodology. The five TEAD tools, described in detail in the Online Tool Development section, include:

1. Energy Use and Emissions Dashboard Widget – Provides segment level real-time and predictive estimates of energy use and emissions that automatically updates every five minutes.
2. Energy Use and Emissions Trend Map – Provides map-based visualization of hourly energy use and emissions on each segment.

3. Energy Use and Emissions Matrix – Provides hourly energy use and emissions estimates aggregated across all road segments.
4. Energy Use and Emissions Charts – Provides breakdown of energy use and emissions across several parameters such as functional road class, hour of day, and day of week.
5. Vehicle Ownership Charts – Provides charts summarizing the annual trends in gas, diesel, hybrid, plug-in hybrid, and electric vehicles.

The general framework of TEAD that summarizes the process of converting transportation data into actionable decision support for sustainability considerations is provided in Figure 1.

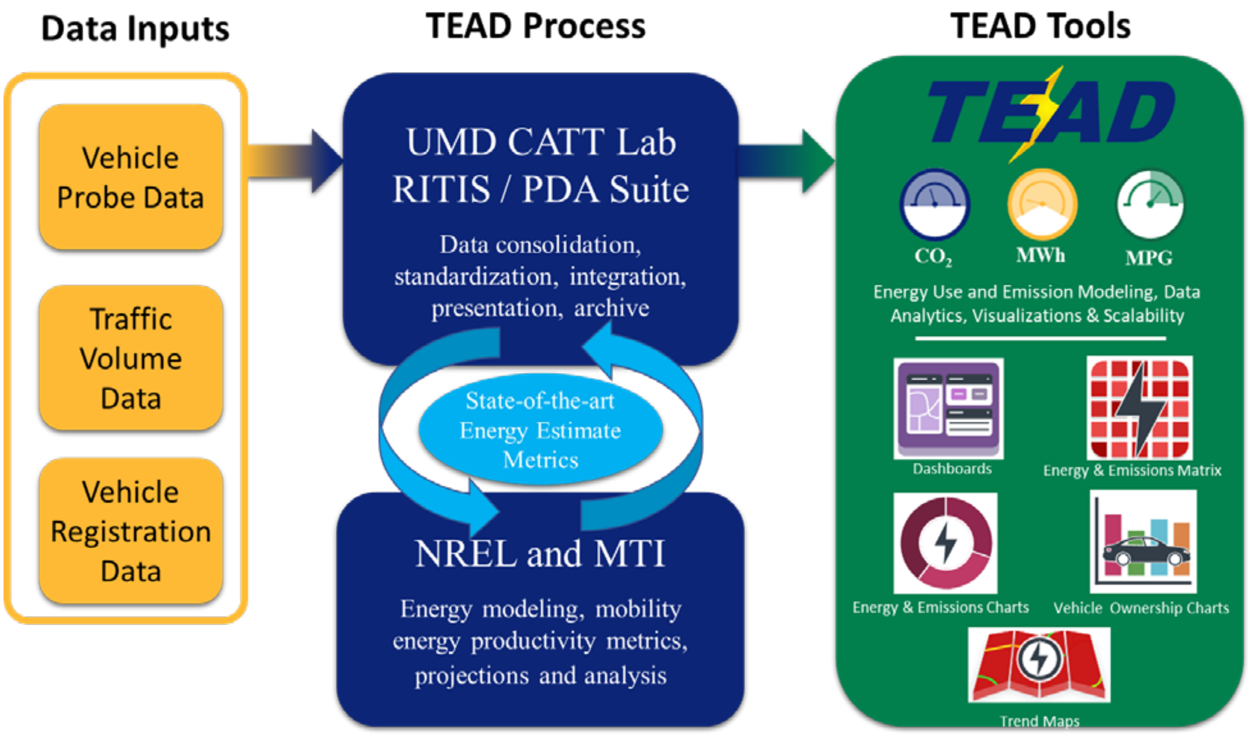


Figure 1: TEAD Framework

The primary objectives of this project were to:

1. Develop and validate methodologies for roadway energy and emissions metrics for historical, real-time, and near future predictive analysis.
2. Create an online tool to measure and visualize transportation energy and emissions metrics.
3. Demonstrate benefits via real-world case studies developed by transportation agency partners.

To achieve these objectives, the research team worked with two stakeholder partners, the Mid-Ohio Regional Planning Commission (MORPC) and the Metropolitan Washington Council of Governments (MWCOG), to ensure the end product met the needs of end users. Upon achieving these objectives, agencies have a viable option for integrating sustainability into their operational and planning decision making process, thus enabling a comprehensive and holistic approach to transportation system analysis.

The two pilot regions included in this project are Columbus, Ohio and the greater Washington, D.C. region (including portions of Virginia and Maryland). Both regions have access to probe data provided by INRIX whom also provides the segment-level volume estimates for this project (in this case volumes from the 2019

INRIX dataset were used). The final data requirement of vehicle registrations was provided by the NREL team under permissions from the third-party data provider, IHS Markit. The annual vehicle registrations from 2014-2017, aggregated at the zip code level, were used to infer the mix of engine types including gas, diesel, hybrid, plug-in hybrid, and electric.

Energy Use and Emission Methodologies

The TEAD tools utilize two models to estimate sustainability metrics. The first model is the Route Energy Prediction Model (RouteE) developed by the National Renewable Energy Lab (NREL). The second model is a Bayesian Energy Use and Emissions Model developed by the Maryland Transportation Institute (MTI). The details of each of these models are described below.

Bayesian Model

Various modal-based emission models have been developed to calculate individual vehicle emissions based on engine-operating mode from driving dynamics (e.g., speed and acceleration). Among these models, the Motor Vehicle Emission Simulator (MOVES) model, a practical emissions estimation application developed by the US Environmental Protection Agency (EPA), is the most widely adopted one. In the MOVES model, vehicle emissions rates are described as a combination of two factors affecting emissions—the emission source (categorized bins by vehicle characteristics such as vehicle types and engine size) and the vehicle operating mode (categorized in bins of second-by-second Vehicle Specific Power, or VSP). Although models of this type capture the driving dynamics in the broad sense, they require very detailed emission rate inputs for every possible combination of emission source and vehicle operating mode. These data usually require a huge amount of memory for storage and powerful computation resources for querying, which are impractical for real-time applications. Furthermore, the data collection process is even harder since it is not feasible to obtain second-by-second travel speed or acceleration. To support real-time emission estimation and short-term emission prediction on large-scale network, a simplified MOVES-based emission model is developed utilizing the Bayesian method. Assuming the VSP distribution on a link generally follows the normal distribution, the influence of other factors can be described using correction factors. Leveraging the driving data (e.g., travel speed and emission consumption) collected from on-board logging system, the correction factors are pre-calculated through the Bayesian model. The MOVES-based Bayesian model takes traffic speed, traffic volume, and link-based features as inputs, and estimates six categories of emission consumption.

The Bayesian model trained on trajectory data with second-by-second travel dynamics collected by GPS-enabled smartphone applications is utilized as input data for training the MOVES-based Bayesian Model. The data includes detailed travel dynamics for each trip, such as speed, acceleration, longitude, latitude, and timestamp. Other information regarding vehicle conditions such as vehicle type, vehicle age and fuel type are also available by querying the user registration records. A total of 2,753 trips were collected from October 2019 to January 2020. Detailed information of the collected data is summarized in Table 1.

Table 1: Summary of Trip Trajectory Data for Model Training

Characteristics	Sedan	SUV	Van	Truck
Number of trips collected	2,197	418	92	46
Number of drivers recorded	151	41	7	9
Average vehicle age (year)	5.53	5.27	7	10
Number of days recorded	120	91	29	26
Number of road segments covered	32597	21,120	5,383	3,032
Total of vehicle miles traveled (mile)	26,135	7,634	731	377
Total of vehicle hours traveled (hour)	1,210	308	34	27
Average trip length (min)	33	44	22	35
Average trip distance (mile)	11.89	18.26	7.94	8.19

To achieve high accuracy in short-term prediction of energy consumption, a traffic dynamic prediction module is integrated, which takes the historical speed and volume as inputs. The historical travel speed data for September and October 2019 is collected from the Regional Integrated Transportation Information System (RITIS) website. The data is at 5-minute intervals and covers the 26,985 TMC links in the Washington metropolitan region. Additionally, the historical daily traffic volume with 15-minute intervals for 2019 was queried from RITIS.

The trip trajectories are matched with TMC links through various spatial-index methods to obtain geometry information. The second-by-second GPS points are snapped on the network system using the built-in Rtree function in Python, which calculates the distance between points and links with bounding boxes. In addition to the Rtree function, the team also compares the point-to-point travel direction and link azimuth to increase the snapping accuracy. The missing values of GPS points are filled in using the traffic information of adjacent points. For each GPS point, the VSP is calculated using the speed and acceleration through the following function defined in MOVES:

$$VSP=v\times[1.1a+9.81\times g(\%)+0.132]+0.000302\times v^3 \quad (1)$$

Based on the goals of the TEAD project, which aimed at producing both real-time and near-term future energy consumption prediction, the team also developed a module to predict the traffic dynamics (i.e., traffic speed and traffic volume). A long short-term memory (LSTM) approach is adopted for predicting traffic speed and volume. In addition to the historical speed and roadway geometry features of the predicted TMC link, the speed of the surrounding TMC links within the 1-mile buffer were included as the inputs for model generation. Similarly, another LSTM-based prediction model was developed to forecast traffic volume. For online application, the LSTM model queries the historical and real-time traffic dynamics data from RITIS and produces short-term prediction of traffic dynamics for the computation module.

The energy consumption estimates are then used to derive CO_2, NO_X, PM2.5, PM2.5 precursor for NO_X, and VOC emissions using the procedure described below:

Step 1. Estimate Adjustment Factors Using Bayesian Model

The MTI team first develops a Bayesian model to calculate the correction factors regarding the influence of the various factors on VSP distribution. The model takes six features as training inputs: traffic speed, traffic volume, functional class, speed limit, departure time, and intersections. The training output is the ratio between energy consumption using actual VSP distribution and normalized VSP distribution.

Step 2. Match Traffic Dynamics, Geometry Features, and Adjustment Factors

The traffic dynamics (i.e., traffic speed and traffic volume) and roadway geometry features (e.g., number of lanes, speed limit, functional class, traffic control, and length) are matched for all TMC links. The adjustment factors extracted from the Bayesian model are then matched with TMC links based on the six features mentioned in Step 1.

Step 3. Estimate Link-based Energy and Emissions

The fleet age distribution for the Washington metropolitan region, together with link-based traffic speed, are utilized to produce link-based VSP distribution, then to achieve link-based operation mode. Using the conversion between operation mode and emissions factors from the MOVESLite emission model [2, 3], the link-based energy consumption for a 15-minutes interval is formulated as below:

$$E_i = \sum_{j \in J} (V_{ij} * e_j * f_i) \tag{2}$$

Where E_i is the energy consumption and f_i is the adjustment factor of link i. V_{ij} represents the traffic volume under operation mode j on link i, and e_j denotes the emission factor of operation mode j. The emissions statistics for CO_2 and NO_X are calculated similarly, using the emission factors from the MOVESLite emission model. For the other three pollutants (i.e., PM2.5, PM2.5 NO_X precursors, and VOC) that are not specified in the emission model noted above, the aggregated emission factors used in the 2017 TDM analysis [4] are utilized to estimate emissions statistics, as shown in the Table 2:

Table 2: Aggregated Emission Factors

Emission Factors	**PM2.5**	**PM2.5 NO_X**	**VOC**
Running (gm/mile)	0.2019	0.0115	0.0688

RouteE Model

The RouteE software package enables accurate estimation of energy consumption for a variety of vehicle types over trips or sub-trips where detailed drive cycle data are unavailable [5,6,7]. Creating a RouteE vehicle model involved training the model over a large set of energy consumption data in a wide variety of operating conditions. Recognizing that such comprehensive on-road fuel consumption data was not available at the time of this study, roughly one million miles of second-by-second driving profiles derived from the Transportation Secure Data Center (TSDC) were simulated with different vehicle models from NREL's Future Automotive Systems Technology Simulator (FASTSim) [8]. These simulations provided energy consumption behavior over a representative sample of driving conditions for the United States. For this project, the RouteE model was further trained using field collected energy use data from 2,500 vehicle trips in the greater Washington, D.C. region, described in the previous Bayesian Model section.

To estimate the energy consumption of a given route, trained RouteE models were applied to a given input dataset with the necessary attributes of segment speed, volume, and engine classification. This was done by creating an Application Programming Interface (API) for RouteE through which the TEAD backend could request the energy estimation results based on the input parameters for a given scenario. This process is summarized in Figure 2. The RouteE API is open to the public as well. The documentation for the RouteE API [9] is available at https://developer.nrel.gov/docs/transportation/routee-v1/.

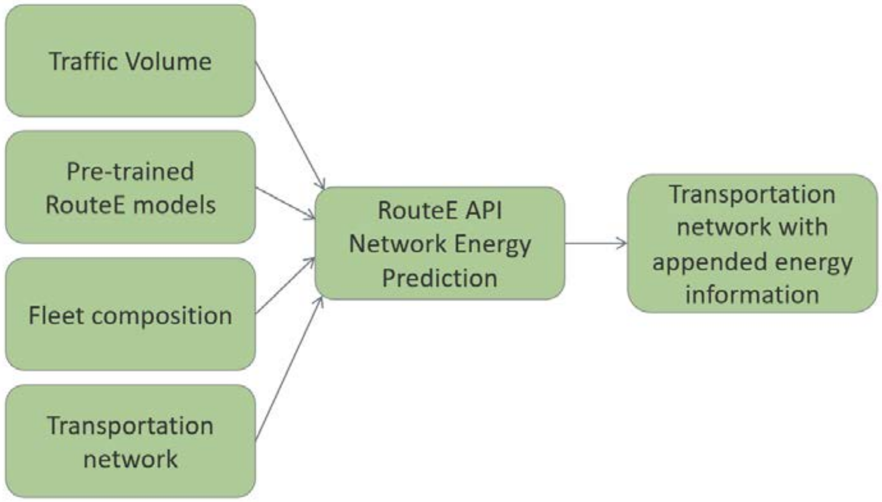


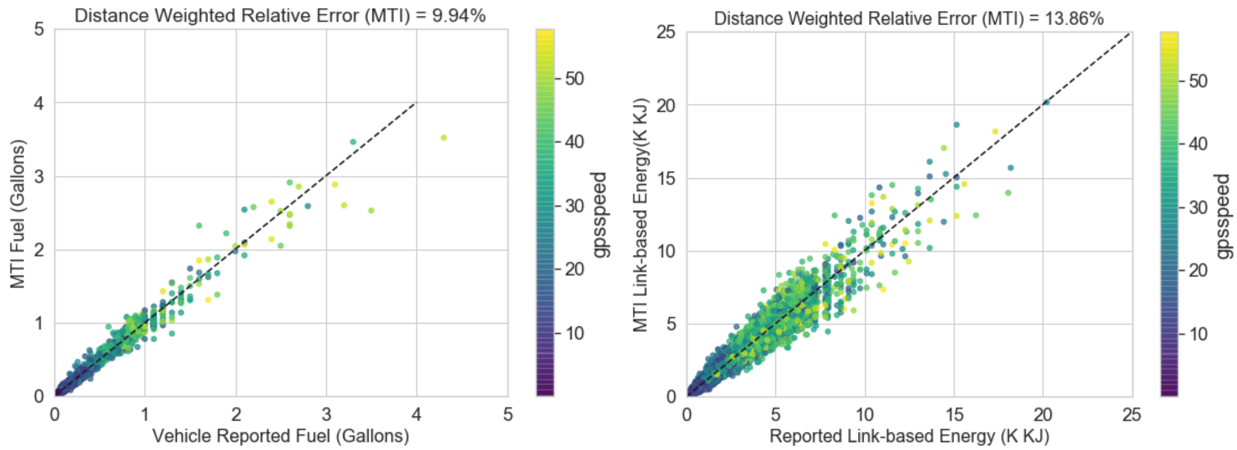
Figure 2: RouteE Energy Estimation Workflow

Validation Results and Discussion

Before the Bayesian and RouteE models could be integrated into online tools, a validation analysis was conducted. Here, field collected energy use records were used to validate model estimates. The second-by-second trajectory points were snapped to the network system using spatial-joining methods to achieve the observed energy consumption of each roadway segment. The roadway geometry information (e.g., number of lanes, speed limit, functional class, and turning movement), together with the traffic dynamic information (i.e., historical speed and volume records derived from RITIS website), were fed into the both the RouteE and Bayesian models as inputs. The predicted results were compared with observed values from energy consumption data at both the link and trip levels. The accuracy was measured by the equation below:

$$e = \sum \left(\left[\frac{d_i}{\sum d} \right] \left| \frac{y_i - \hat{y_i}}{\hat{y_i}} \right| \right) \tag{3}$$

Where d_i refers to the driving distance of $trip_i(link_i)$, and $\sum d$ is the total driving distance of all trips (links) in the validation dataset. $\hat{y_i}$ and y_i denote the observed and predicted fuel consumption of $trip_i(link_i)$. The error term in the equation is the distance-weighted relative error, which removes the error sensitivity to different trip distance (i.e., short-distance trip or link usually has higher error). Figure 3 shows the distance-weighted relative error at link and trip levels.



(a) (b)

Figure 3: Scatter plots of distance-weighted relative errors for (a) trip-level prediction, and (b) link-level prediction

RouteE was also validated against vehicle-reported fuel consumption data. The trip error plot (Figure 4) shows trip-level energy prediction results for a variety of vehicles (unknown make/models). These results are for one conventional RouteE model that "best fit" the heterogeneous fleet of unknown vehicles. Trip accuracy would improve if vehicle year, make, model information was available for this dataset, but the results nevertheless demonstrate that RouteE can provide meaningful energy consumption estimates even in the absence of vehicle information.

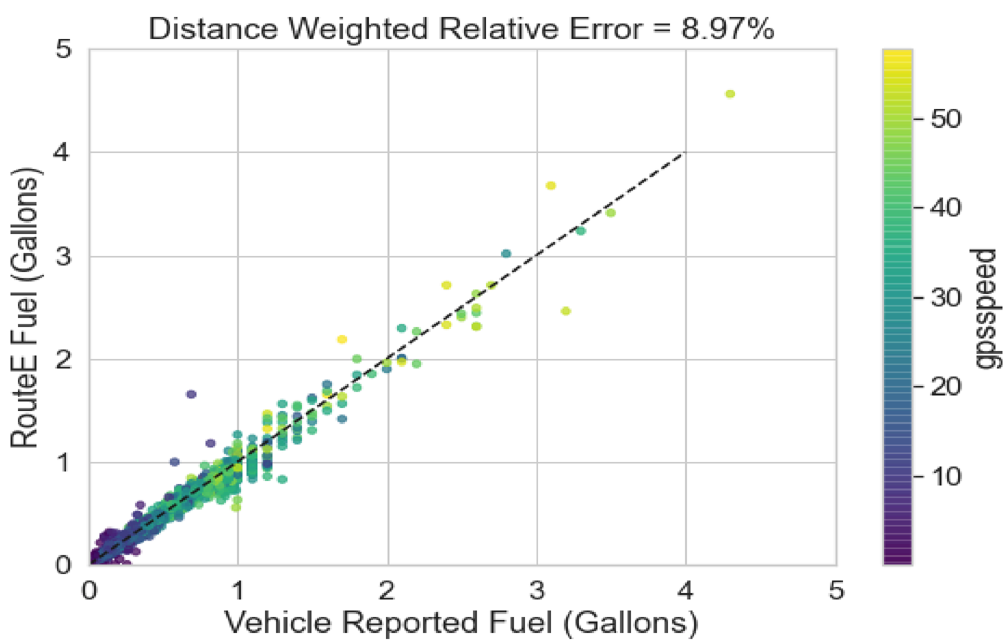
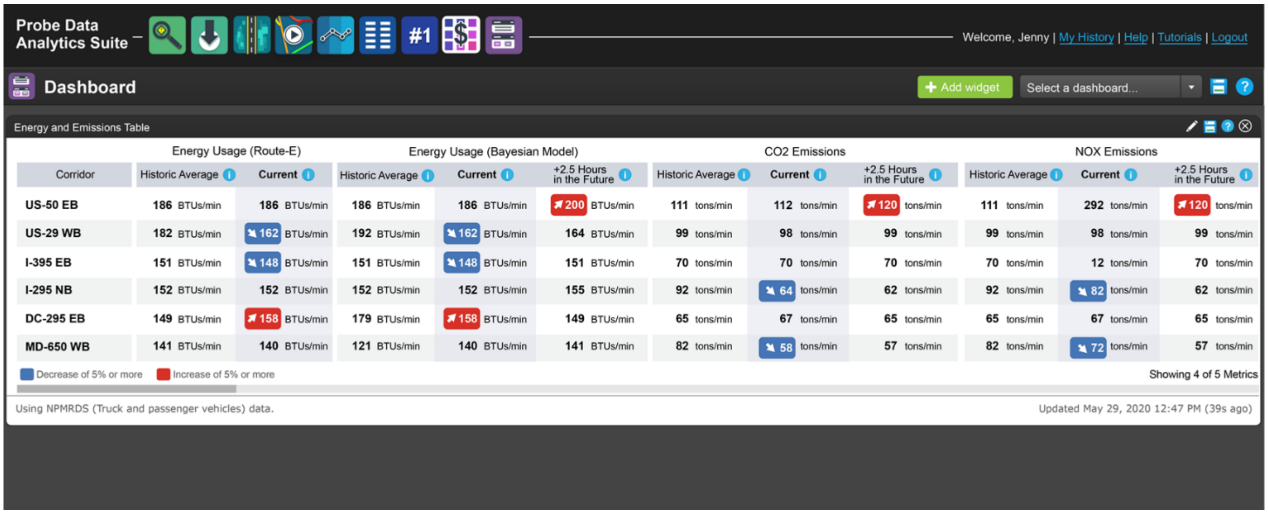


Figure 4: RouteE Energy Predictions Compared to On-Road Data

Online Tool Development

This project created five online tools for automated transportation sustainability analysis. These five tools are:

1. Energy Use and Emissions Dashboard Widget – The Energy Use and Emissions Dashboard Widget (Figure 5) provides real-time, historical, and predictive energy use and emissions from the driving mode that automatically updates every five minutes.



	Energy Usage (Route-E)		Energy Usage (Bayesian Model)			CO2 Emissions			NOX Emissions		
Corridor	Historic Average	Current	Historic Average	Current	+2.5 Hours in the Future	Historic Average	Current	+2.5 Hours in the Future	Historic Average	Current	+2.5 Hours in the Future
US-50 EB	186 BTUs/min	186 BTUs/min	186 BTUs/min	186 BTUs/min	200 BTUs/min	111 tons/min	112 tons/min	120 tons/min	111 tons/min	292 tons/min	120 tons/min
US-29 WB	182 BTUs/min	162 BTUs/min	192 BTUs/min	162 BTUs/min	164 BTUs/min	99 tons/min	98 tons/min	99 tons/min	99 tons/min	98 tons/min	99 tons/min
I-395 EB	151 BTUs/min	148 BTUs/min	151 BTUs/min	148 BTUs/min	151 BTUs/min	70 tons/min	70 tons/min	70 tons/min	70 tons/min	12 tons/min	70 tons/min
I-295 NB	152 BTUs/min	152 BTUs/min	152 BTUs/min	152 BTUs/min	155 BTUs/min	92 tons/min	64 tons/min	62 tons/min	92 tons/min	82 tons/min	62 tons/min
DC-295 EB	149 BTUs/min	158 BTUs/min	179 BTUs/min	158 BTUs/min	149 BTUs/min	65 tons/min	67 tons/min	65 tons/min	65 tons/min	67 tons/min	65 tons/min
MD-650 WB	141 BTUs/min	140 BTUs/min	121 BTUs/min	140 BTUs/min	141 BTUs/min	82 tons/min	58 tons/min	57 tons/min	82 tons/min	72 tons/min	57 tons/min

Figure 5: Real-time and Predictive Dashboard Widget

2. Energy Use and Emissions Trend Map – The Energy Use and Emissions Trend Map (Figure 6) creates hourly animations of energy use and emissions on selected roads and date ranges. The maps can be exported to animated GIFs and MP4s.

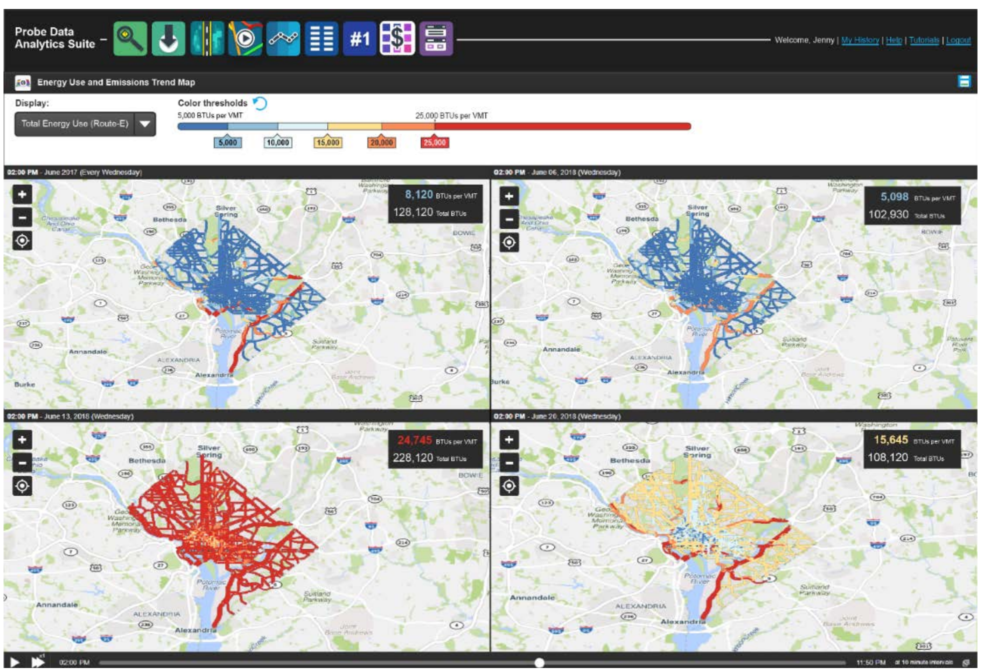


Figure 6: Energy Use and Emissions Trend Map

3. Energy Use and Emissions Matrix – The Energy Use and Emissions Matrix (Figure 7) creates a color-coded matrix of aggregated energy use and emissions estimates for all roads for each hour within the user-defined analysis period.

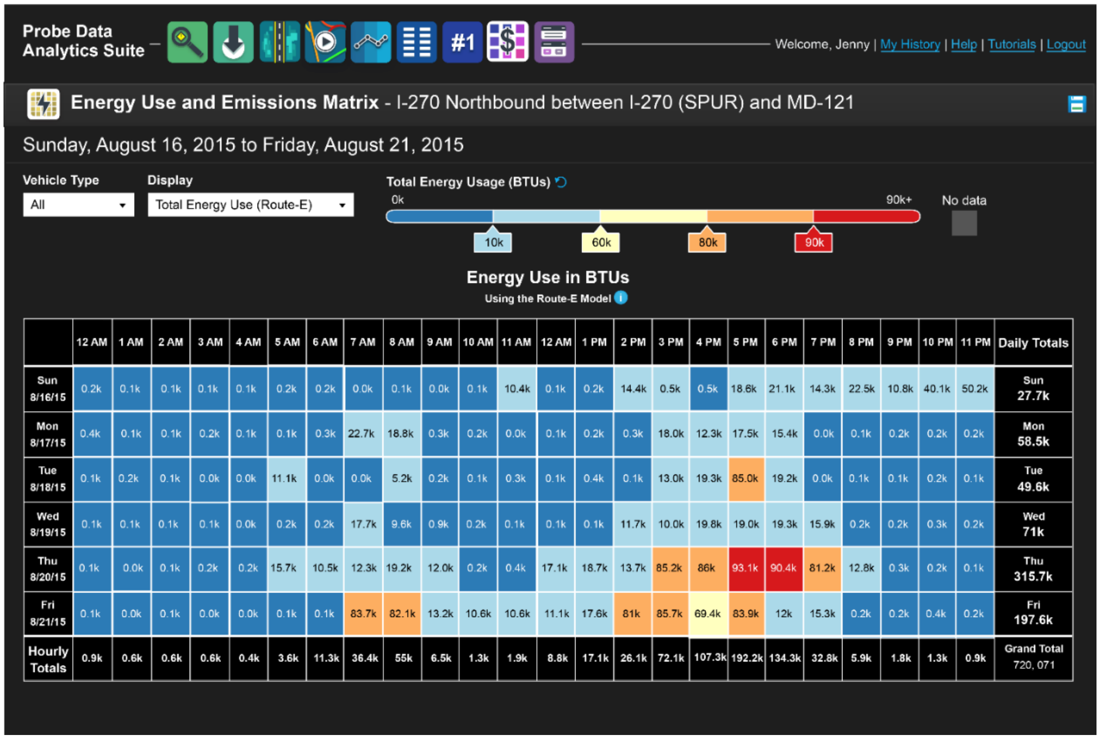


Figure 7: Energy Use and Emissions Matrix

4. Energy Use and Emissions Charts – The Energy Use and Emissions Charts (Figure 8) develop charts that break down energy use and emissions by road class, engine type, hour of day, day of week, and month.

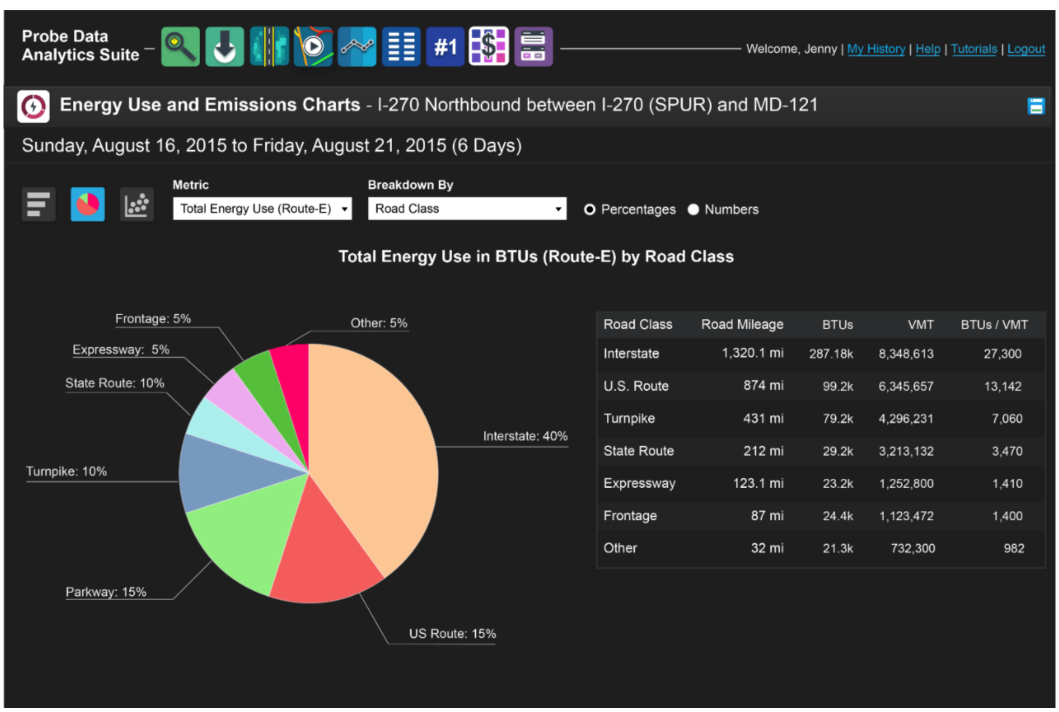


Figure 8: Energy Use and Emissions Charts

5. Vehicle Ownership Charts – The Vehicle Ownership tool (Figure 9) supports annual trend analysis of vehicle ownership (by inferred engine type) in user-defined regions.

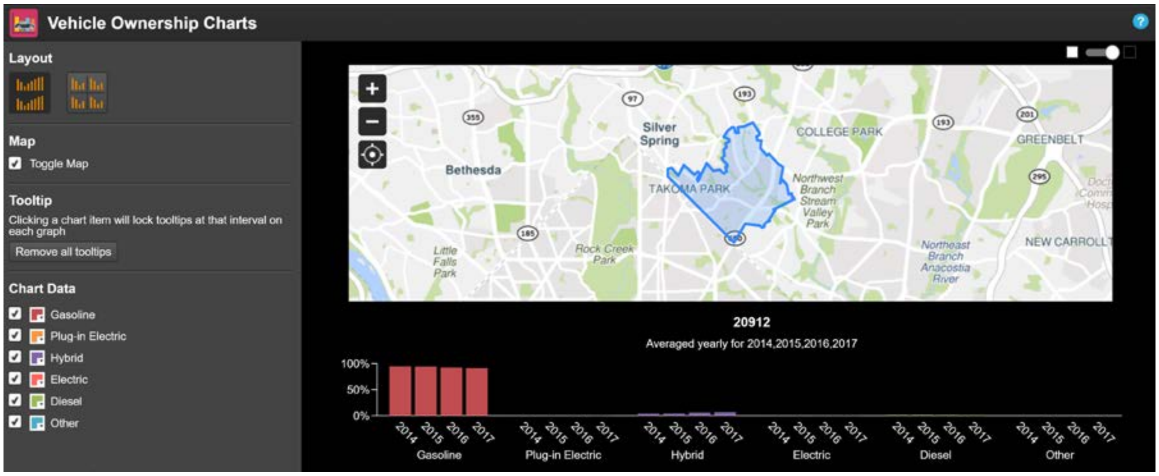


Figure 9: Vehicle Ownership Charts

The creation of these tools required the development of a comprehensive system that enables users to request energy use and emissions outputs for specific road segments and times ranges. To do so, the development effort required front-end interface work as well as back-end data processing and sharing work achieved by APIs.

Real-World Use Cases

To illustrate the application of these tools, the following real-world use cases are provided.

Snooper Truck Crash and Fire on Woodrow Wilson Bridge

This use case illustrates the use of the Energy Use and Emissions Matrix tool to assess a major crash event. This crash occurred on Wednesday, June 18, 2018, at 10:50am on the Woodrow Wilson Bridge (outer loop portion of I-495, Capital Beltway). This major crash event involved a tractor trailer that penetrated a mobile work zone set up for bridge inspections. The tractor trailer crashed into the impact attenuating truck and struck the inspection vehicle (i.e., snooper truck) causing a vehicle fire. The major crash caused the closure of the outer loop of I-495 and took nearly 12 hours to clear the scene. The crash caused widespread congestion across the National Capital Region, especially on the alternative routes. To assess the impacts of this crash on CO_2 emissions, the Energy Use and Emissions Matrix tool was employed to compare the emissions on the day of the crash versus that on a typical day. The previous Wednesday June 13, 2018 was used for comparison. As shown in Table 3, an increase of 38.3% in CO_2 was observed. It is worth noting that these CO_2 estimates assume the traffic demand was the same for these two days.

Table 3: CO_2 Emissions Analysis Using the Matrix Tool

	CO2 Emissions (tons)												
	11 AM	12 PM	1 PM	2 PM	3 PM	4 PM	5 PM	6 PM	7 PM	8 PM	9 PM	10 PM	Total
6/13/2018	112.4	116.0	123.4	135.1	156.2	164.9	166.9	135.6	106.2	86.8	70.0	51.5	9536.5
6/20/2018*	120.0	135.4	140.7	164.8	190.1	219.7	238.4	201.0	153.8	120.5	84.7	59.5	13193.6
* Day of crash												% Change	38.3%

Covid-19 Impacts

This use case illustrates the application of the Energy Use and Emissions Trend Map Tool for the assessment of changes in energy use before versus during the period of COVID-19 travel impacts. This analysis compares the average weekday in April 2019 (before COVID-19) to the average weekday in April 2020 (during COVID-19). The road segments used in this analysis were northbound I-71 between Jack Gibbs Boulevard and N Broadway Lane and eastbound I-670 between I-71 and I-270 in Columbus, Ohio.

Figures 10 and 11 show the energy use estimates on the target corridors during the 4pm and 5pm hours, respectively. Here shades of blue indicate lower energy use per vehicle mile traveled on each segment while the transition to yellow, orange, and red indicate higher energy use per vehicle mile traveled. Table 4 presents the summary of the change in energy use during these hours before and during COVID-19 impacts. In this analysis, energy use on these corridors were reduced by 33.4% in the 4-6pm hours due to COVID-19 travel restrictions. Similar to the previous use case, these results do not include the impact of volume changes between the analysis dates. Future enhancements will address this limitation by using date specific volume estimates.

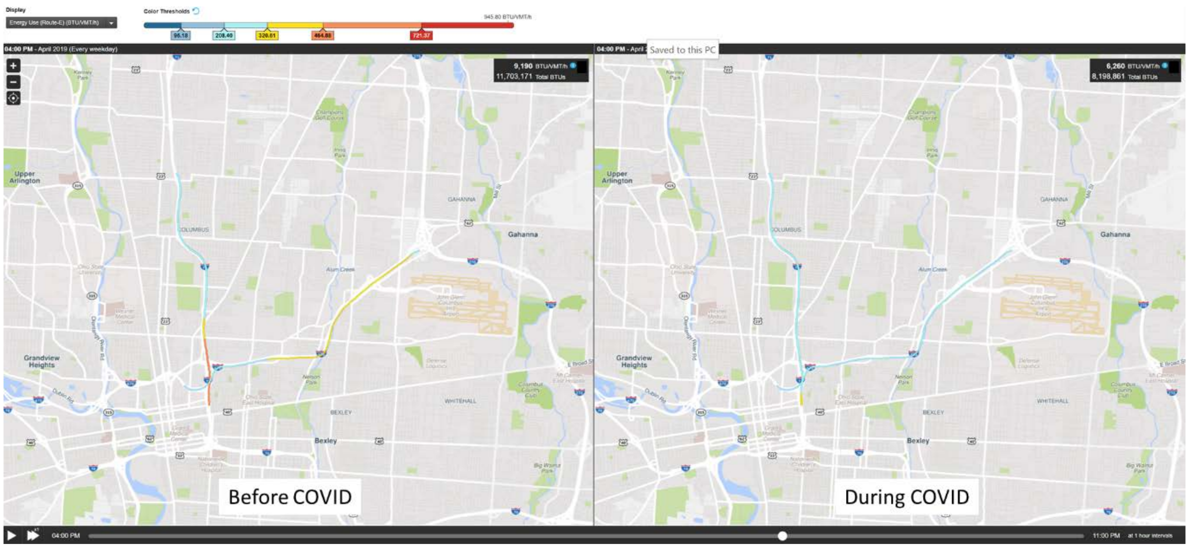


Figure 10: Before versus During COVID-19 Energy Use Comparison Map in Columbus, OH (4pm)

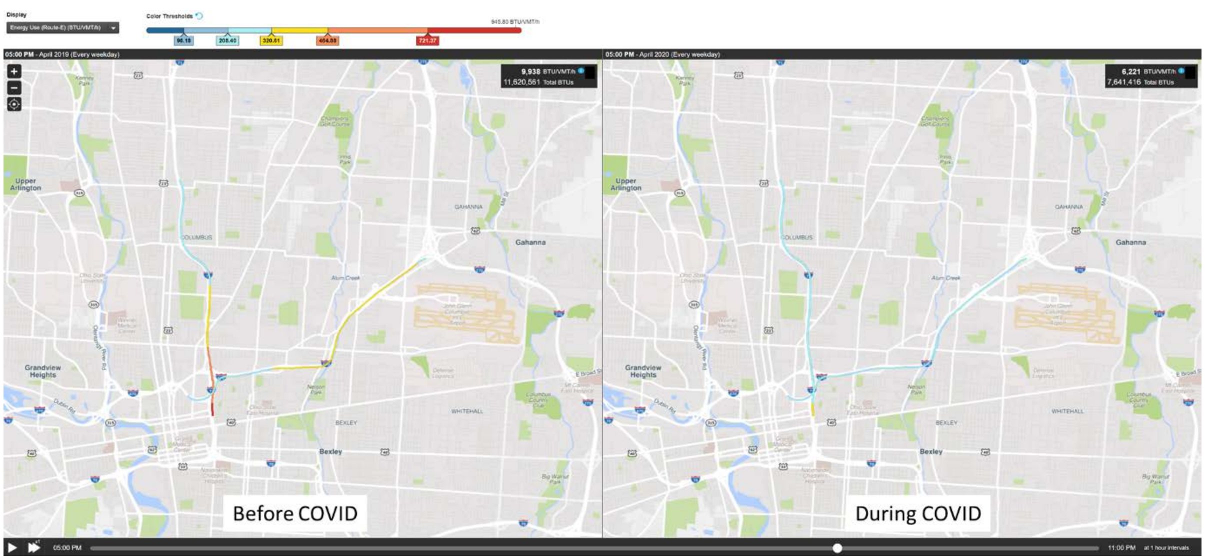


Figure 11: Before versus During COVID-19 Energy Use Comparison Map in Columbus, OH (5pm)

Table 4: Before versus During COVID-19 Energy Use (BTU) per VMT in Columbus, OH

	4:00 PM	5:00 PM	Total
Apr-19	8,809	9,939	18,748
Apr-20	6,261	6,222	12,482
% Change	28.9%	37.4%	33.4%

Conclusions and Next Steps

This project developed methodologies to estimate segment level energy use and emissions using data that most transportation agencies already collect or have access to. These methodologies were integrated into an automated online analysis platform consisting of five distinct tools. The tools were shown to greatly reduce the effort of conducting detailed sustainability analysis without sacrificing estimation accuracy.

Some future research paths include the integration of real-time volume estimation, road grades, enhanced commercial vehicle energy use and emissions modeling, refined signalized intersection energy use and emission modeling, and atmospheric modeling of emissions for validation and air quality analysis.

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