Estimating Truck Energy Consumption and Emissions Using Low-Resolution Speed Data

Sean X. He
Department of Civil and Environmental Engineering
Rensselaer Polytechnic Institute

2022 ITS-NY 29th Annual Meeting
June 17, 2022

Background

In 2019, heavy trucks in the US*:

- Consumed **24%** of the total energy used in transportation sector

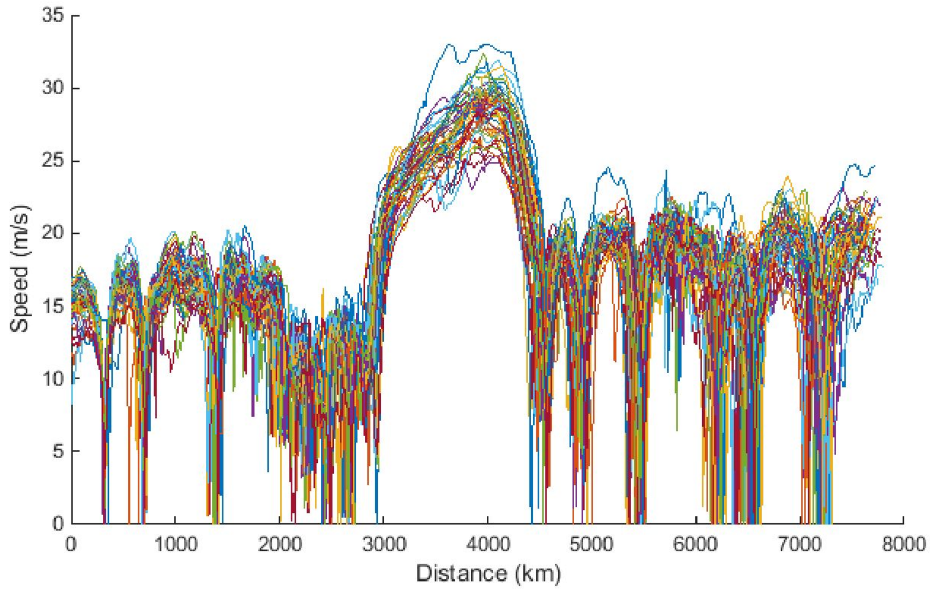
- Emitted **30%** of the total highway GHG emissions

* Transportation Energy Data Book: Edition 40—2022 (ORNL)

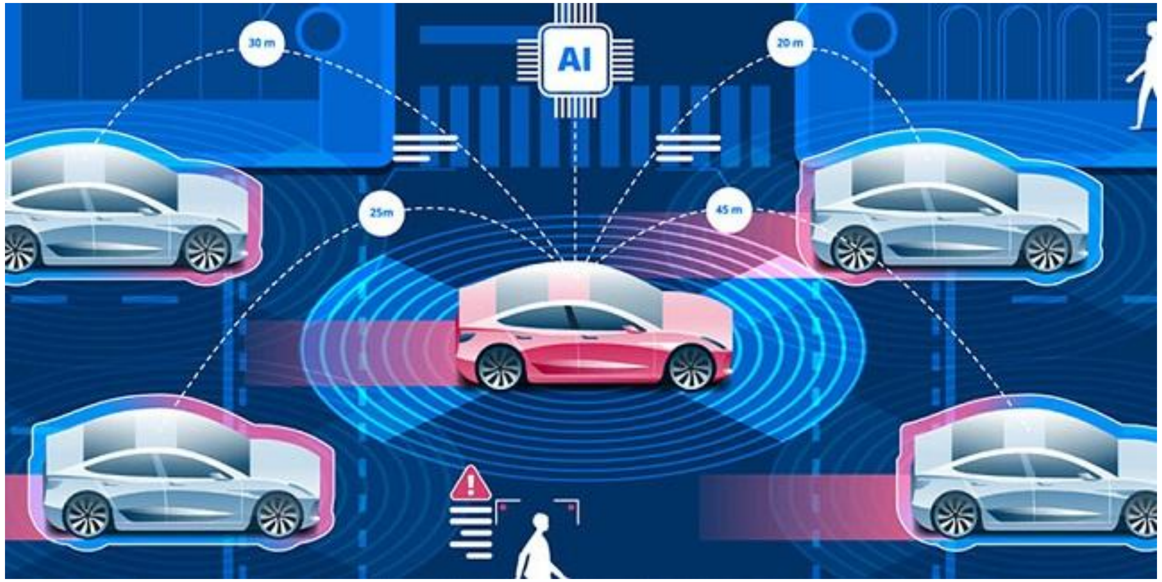
Tools and Software

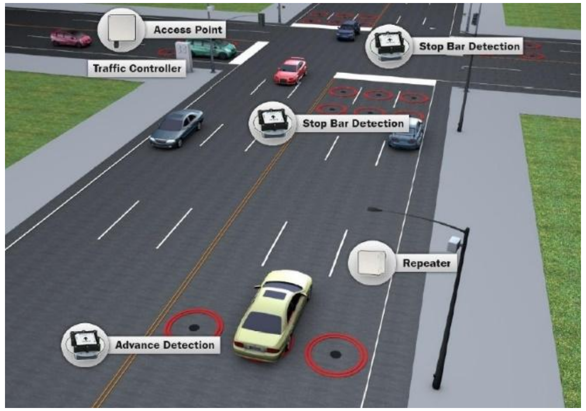
- Fuel consumption and emissions of trucks can be measured by adopting models:
  - MOBILE--US Environmental Protection Agency
  - MOtor Vehicle Emission Simulator (MOVES) -- US Environmental Protection Agency
  - EMission FACtor (EMFAC) -- California Environmental Protection Agency
  - GREET Model – Argonne National Lab

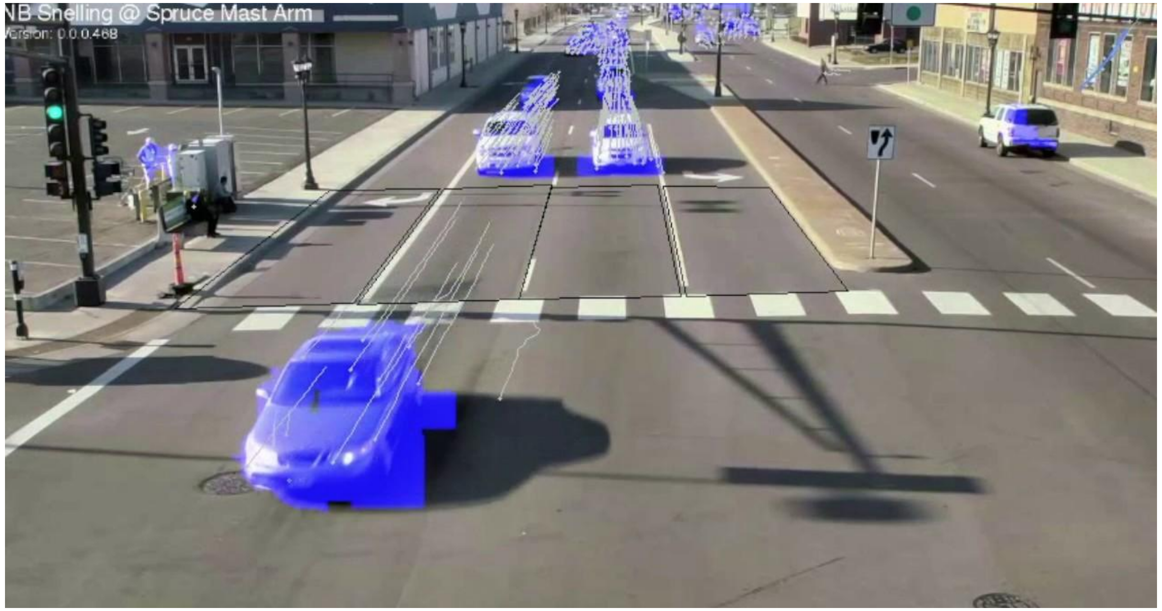
- Typical Data requirement:
  - Microscopic vehicle dynamics data



Data Resources







Challenges in Data Availability

1

Sensor Sparsity

Spatially sparse, cannot cover all truck routes

2

Low Resolution

Sparse in time dimension; cannot provide high-resolution (higher than 1Hz) details

3

Privacy

Applications and platforms may exceed users' expectations

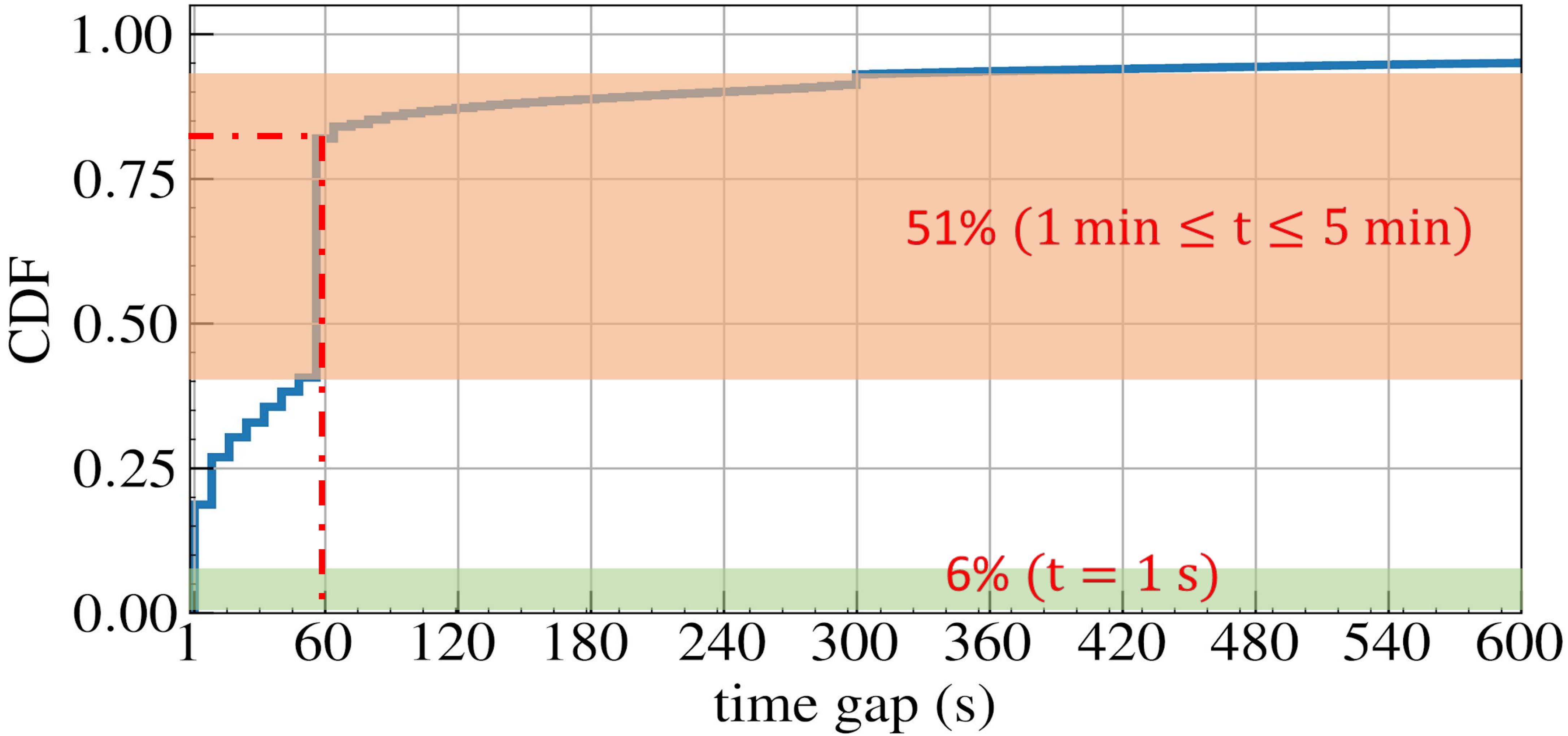
4

Other

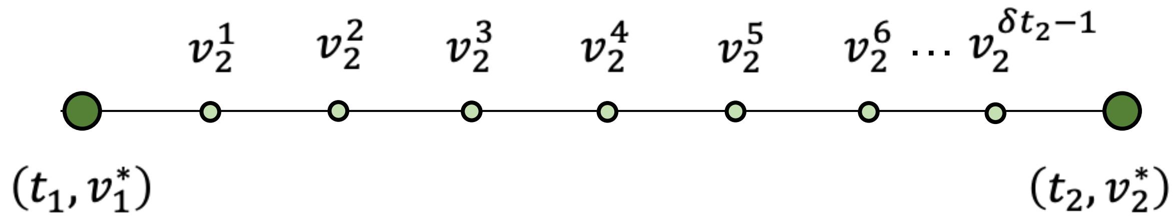
Data security, capacity of storage, device and training costs

Low-Resolution GPS data

ATRI data: 3 Moths, 51,142 trucks, >38 Million records

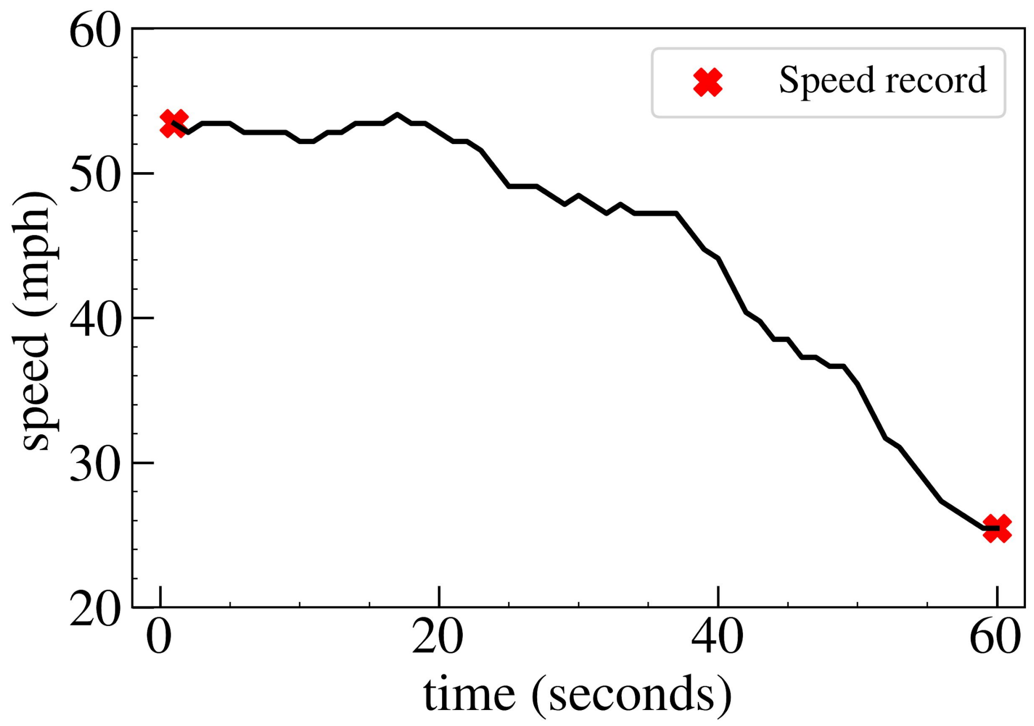


Imputation for Low-Resolution Speed Data



Imputation Process

- "Bridging" the observed speeds, considering:
  - Acceleration constraint
  - Travel distance constraint



- Generalized Brownian bridge process

$$v_i^\tau - v_i^{\tau-1} = \boxed{\mu_i^\tau} \cdot \delta\tau + \boxed{r_i^\tau}\ \delta\tau$$

Drift

Variance

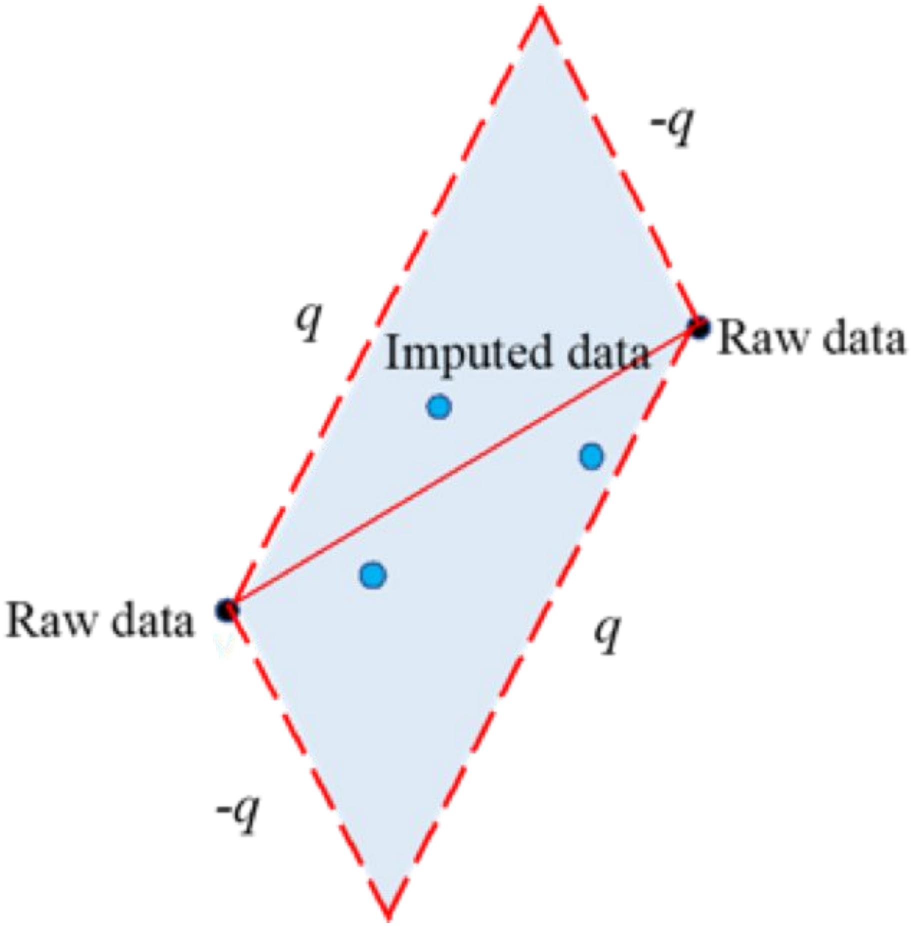
Mazzolo, A., 2017. Constrained Brownian processes and constrained Brownian bridges. J. Stat. Mech. Theory Exp. 2017, 23203.

Acceleration Constraint

$$\left|v_i^\tau - v_i^{\tau-1}\right| \leq q, \qquad \forall\tau$$

Parameter q depends on engine power, terrain, road conditions, etc.

A feasible region of speed trajectory



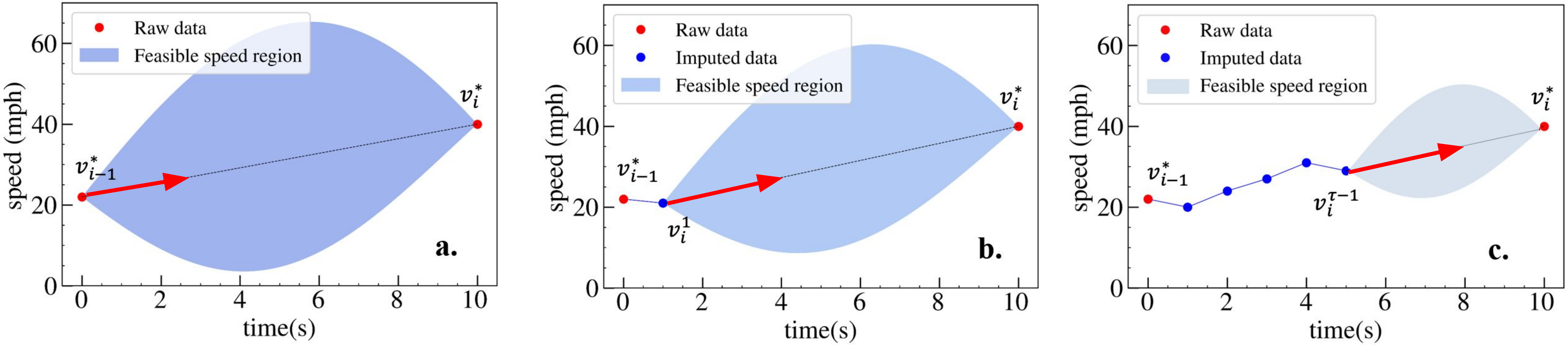
Speed-Affected Drift

First drift to ensure the bridging process converges to end speed

$$v_i^\tau - v_i^{\tau-1} = \mu_i^\tau \cdot \delta\tau + r_i^\tau \cdot \delta\tau$$

$\boxed{\lambda_i^\tau}$ η_i^τ

$$\lambda_i^\tau = \frac{v_i^* - v_i^{\tau-1}}{\delta t_i - \tau + 1}$$

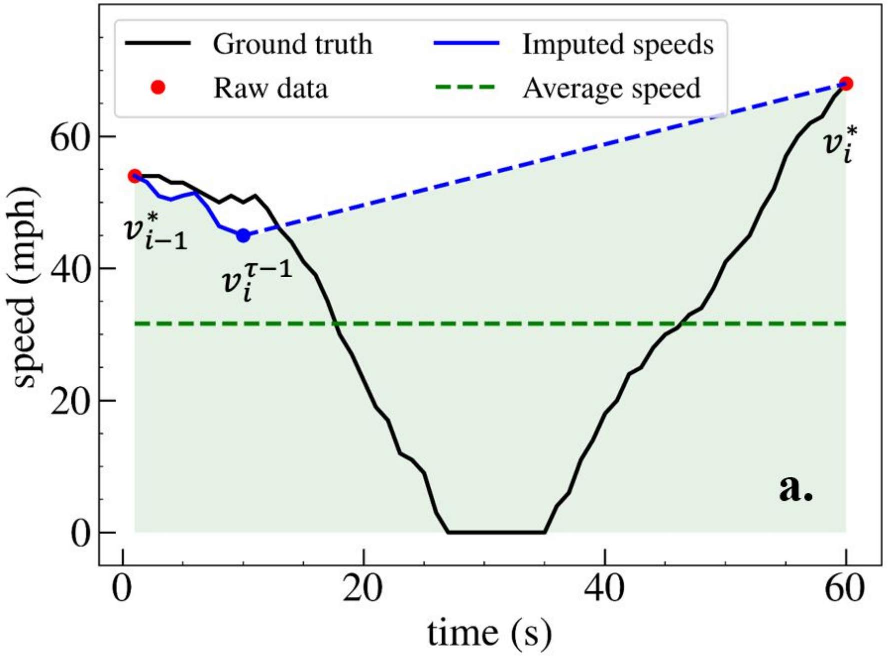


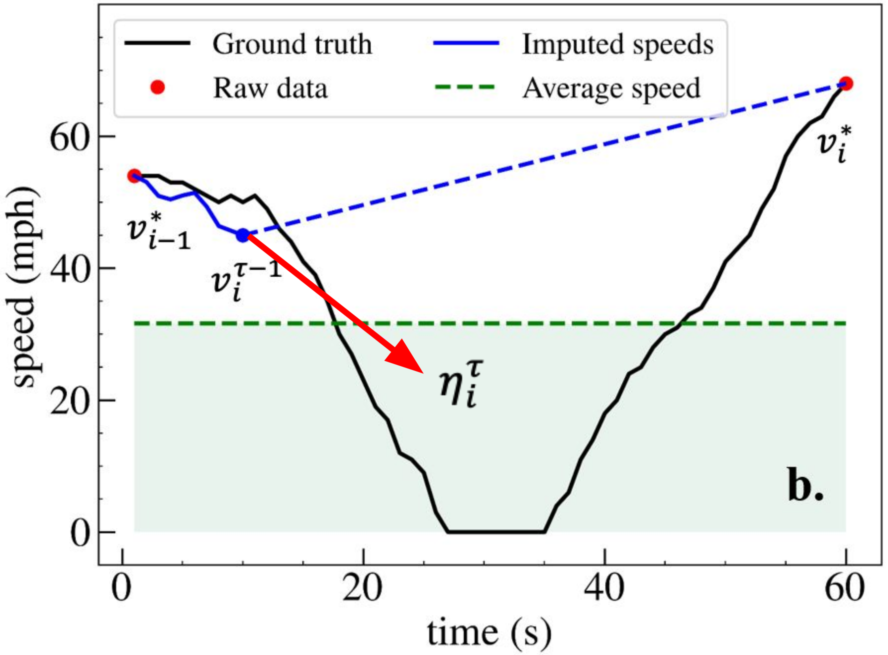
Distance-Affected Drift

Second drift to factor travel distance constraint

$$v_i^\tau - v_i^{\tau-1} = \underbrace{\mu_i^\tau}_{\lambda_i^\tau} \cdot \delta\tau + \underbrace{r_i^\tau}_{\boxed{\eta_i^\tau}} \cdot \delta\tau$$

$$\eta_i^\tau = \alpha \cdot \frac{\delta d_i - \delta \hat{d}_i^\tau}{\delta d_i + \delta \hat{d}_i^\tau}, \qquad \forall \tau = 1, 2 \ldots, \delta t_i - 1$$



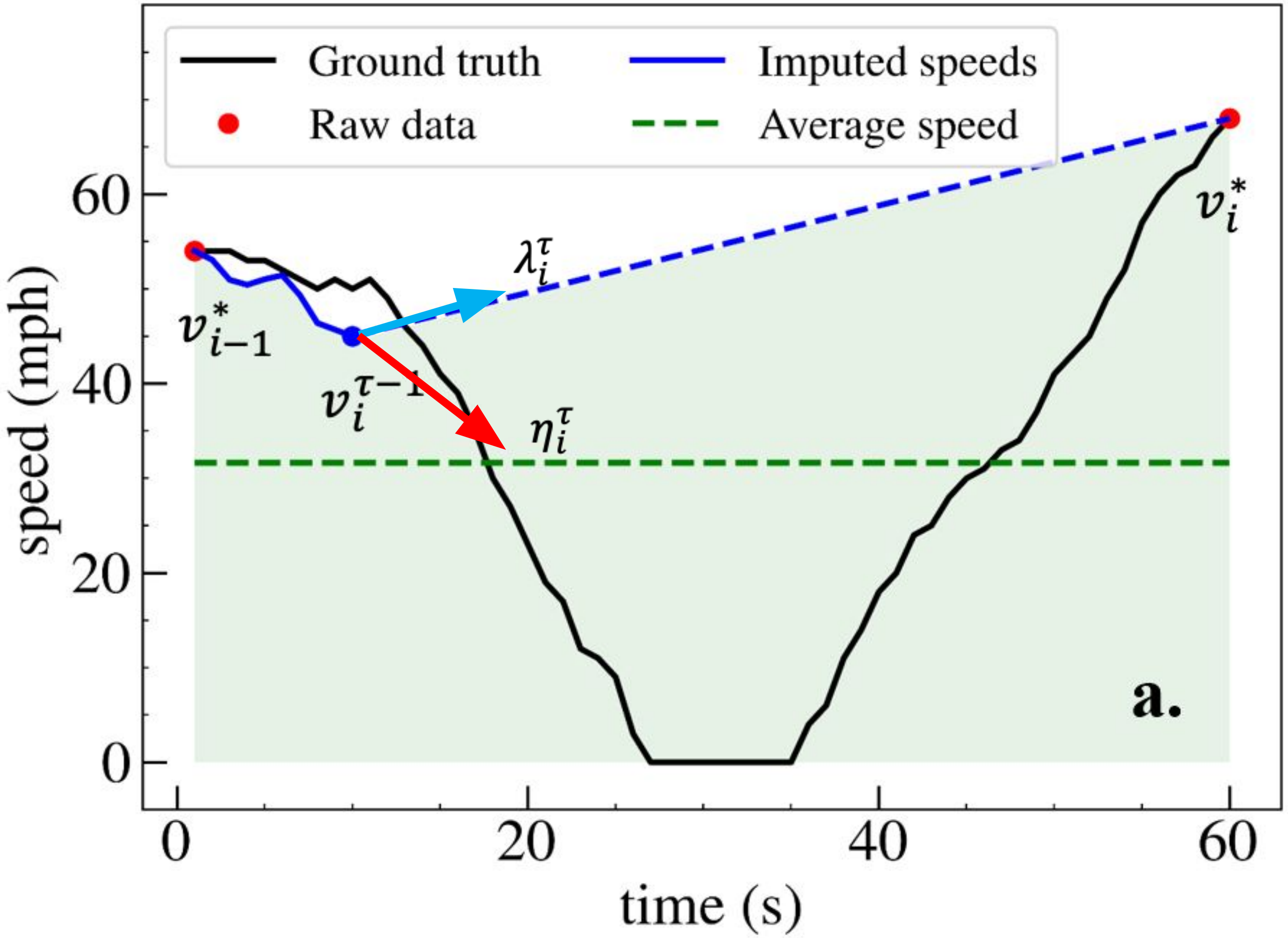


Model Summary

$$\mu_i^\tau = (\lambda_i^\tau + \eta_i^\tau) \cdot \frac{\log_\beta(v_i^{\tau-1} + 1)}{\gamma}$$

$$a_i^\tau = \mu_i^\tau + r_i^\tau$$

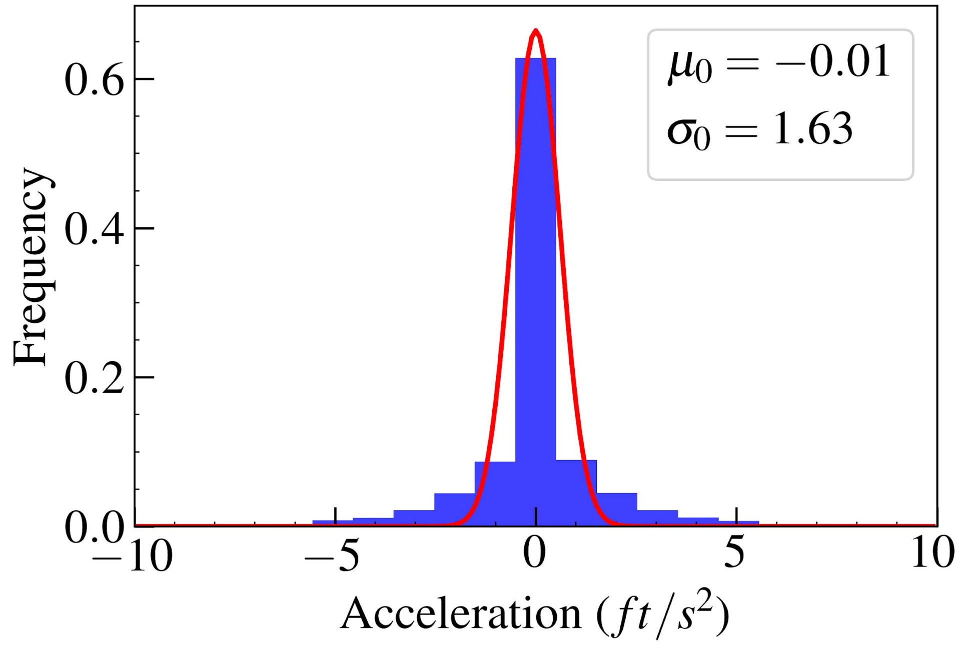
$$\hat{v}_i^\tau = v_i^{\tau-1} + a_i^\tau \cdot \delta\tau$$



$$v_i^\tau = \max\{\min\{\hat{v}_i^\tau, v_i^{\tau-1} + q, upperb_i^\tau\} v_i^{\tau-1} - q, lowerb_i^\tau, 0\}$$

Model Calibration

- **Data:** Second-by-second dataset **‘NYCGPSData’** (Holguín-Veras et al. 2010)
  - 9 truck routes
  - 313,386 second-by-second GPS data
  - Cover New York City area



- **Objective:** Kullback-Leibler divergence

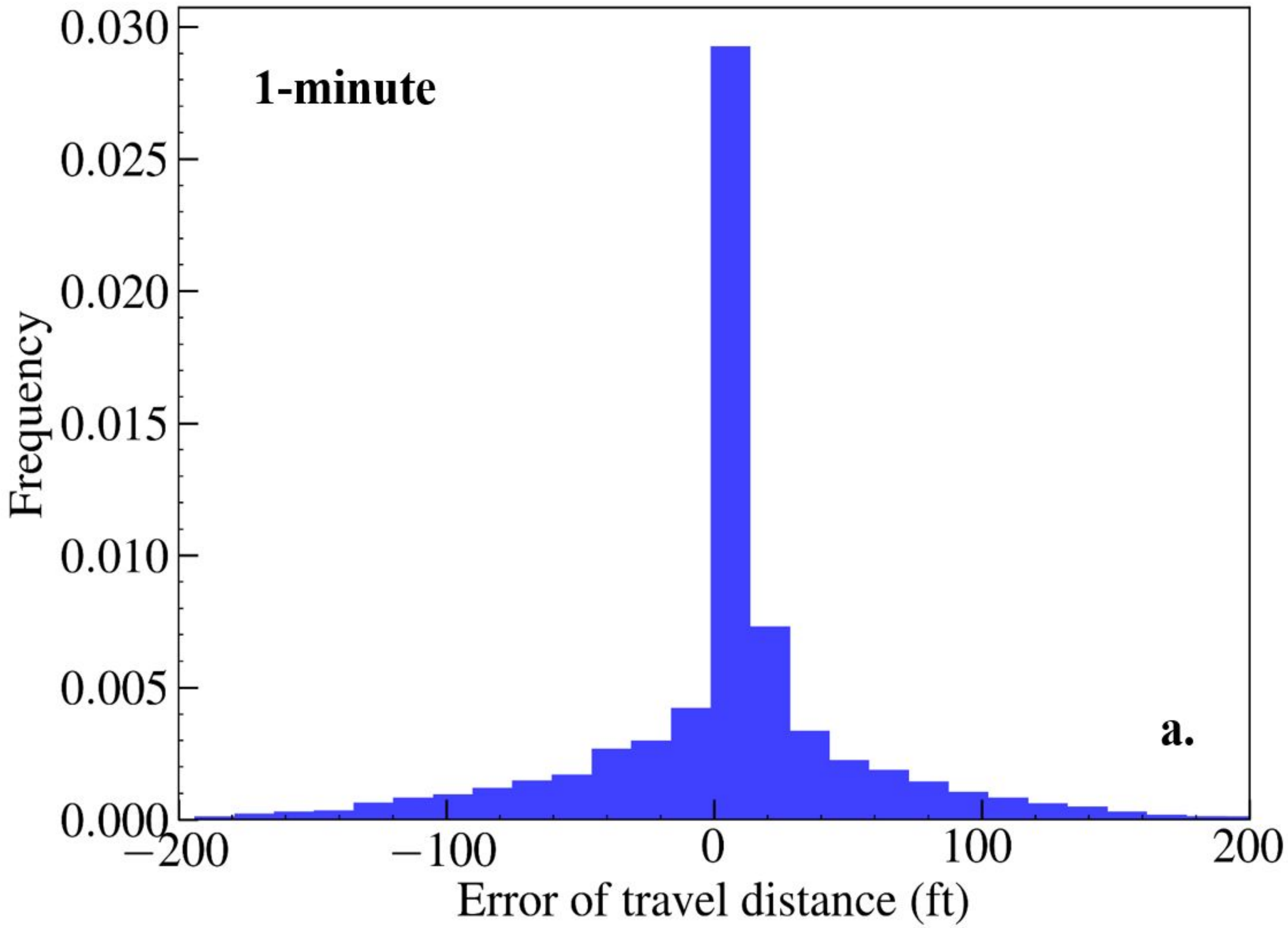
$$D_{KL}(P||Q) = \sum_{x \in \chi} P(x) \log\left(\frac{P(x)}{Q(x)}\right)$$

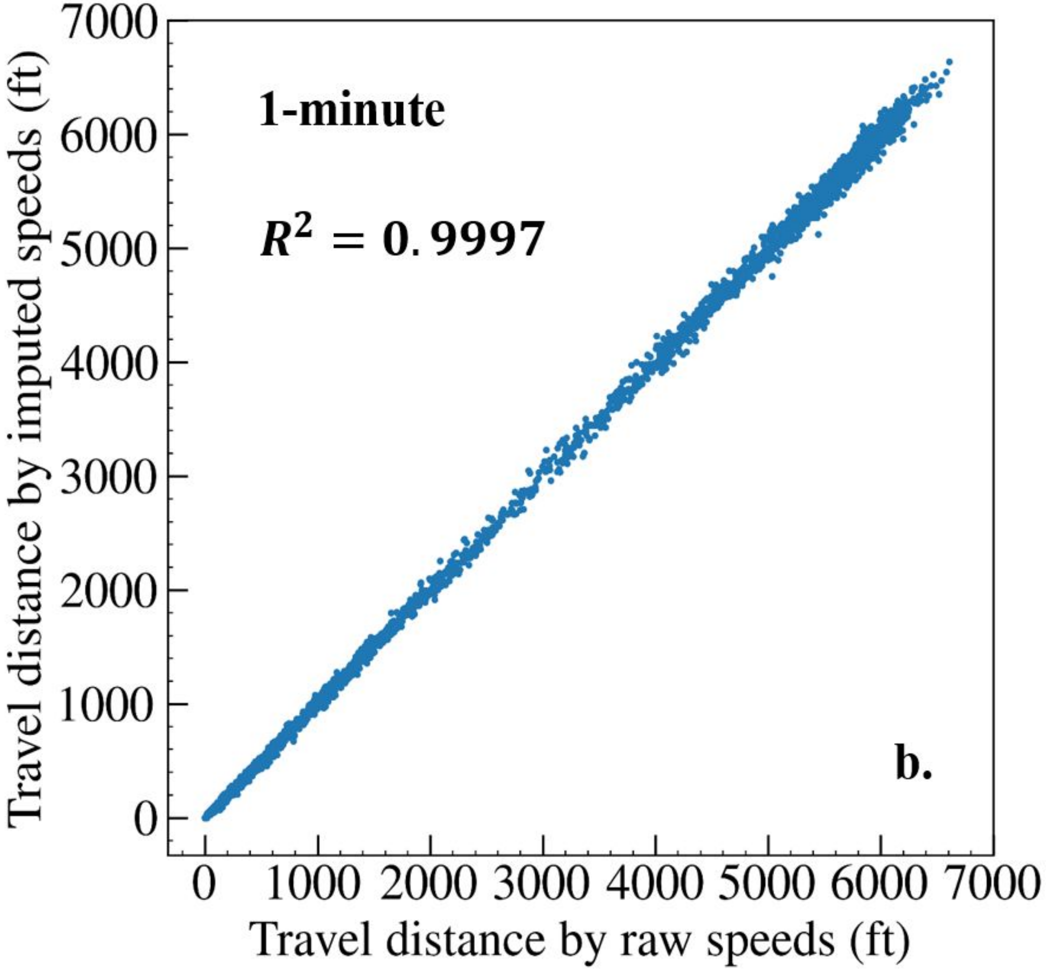
- **Calibrated parameters:**

Parameters				
Value	1.4	19.5	1.7	10.1

Holguín-Veras, J., Ozbay, K., Kornhauser, A., Shorris, A., Ukkusuri, S., 2010. Integrative freight demand management in the New York City metropolitan area.
Kullback, S., Leibler, R., 2006. On information and sufficiency. the annals of mathematical statistics. Ann. Math. Stat. 79–86.

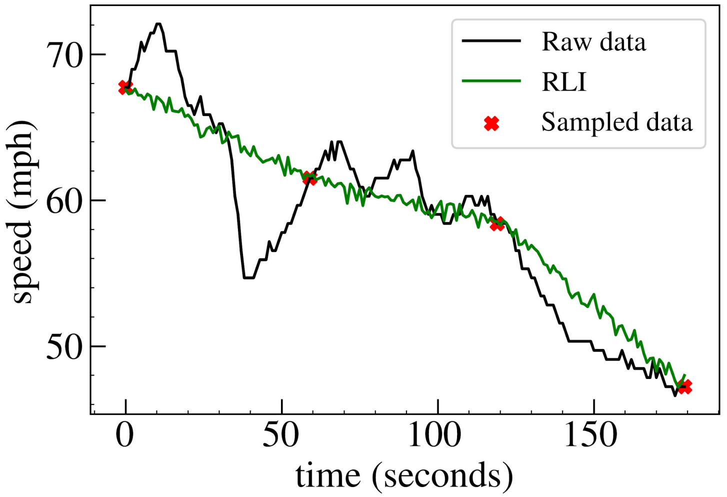
Calibration Results



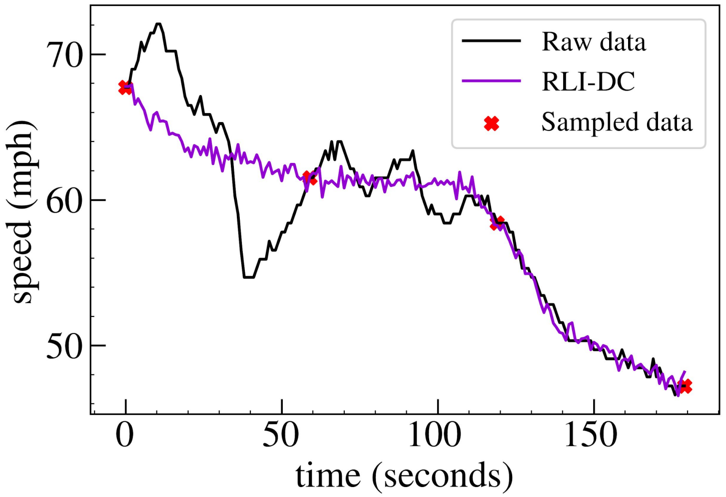


Speed Comparison

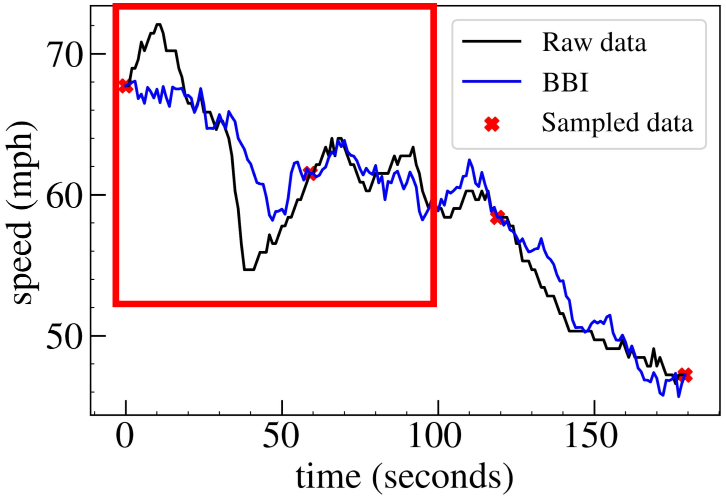
- Randomized linear imputation (RLI)
- Randomized linear imputation with distance constraint (RLI-DC)
- Brownian bridge-based imputation (BBI)



RLI



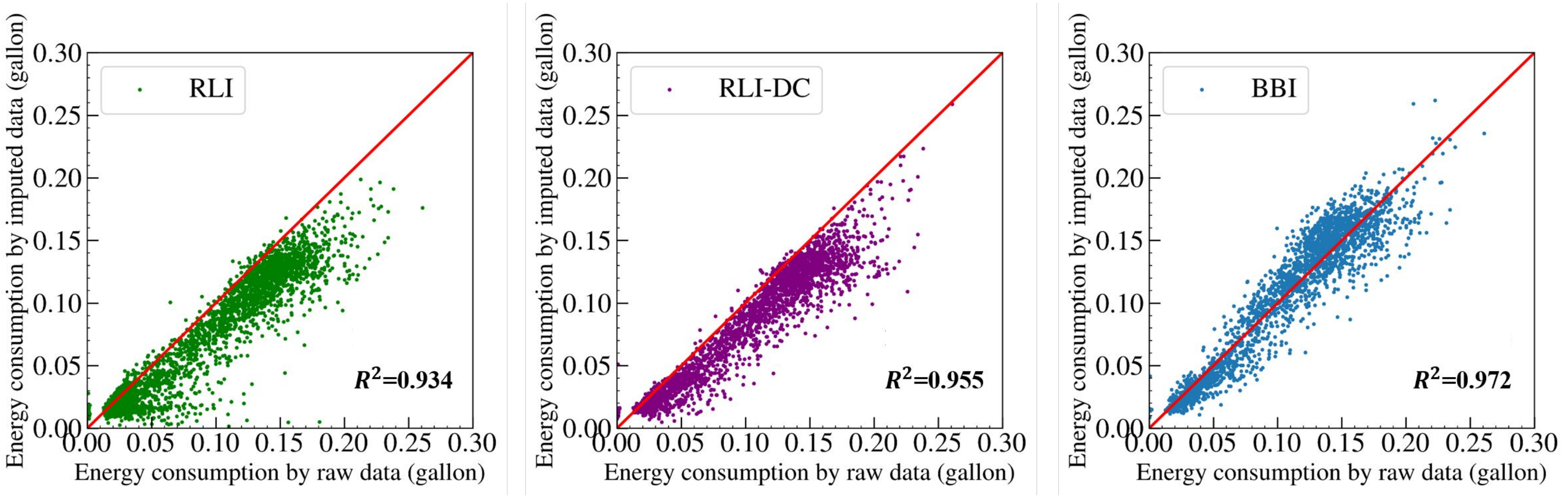
RLI -DC



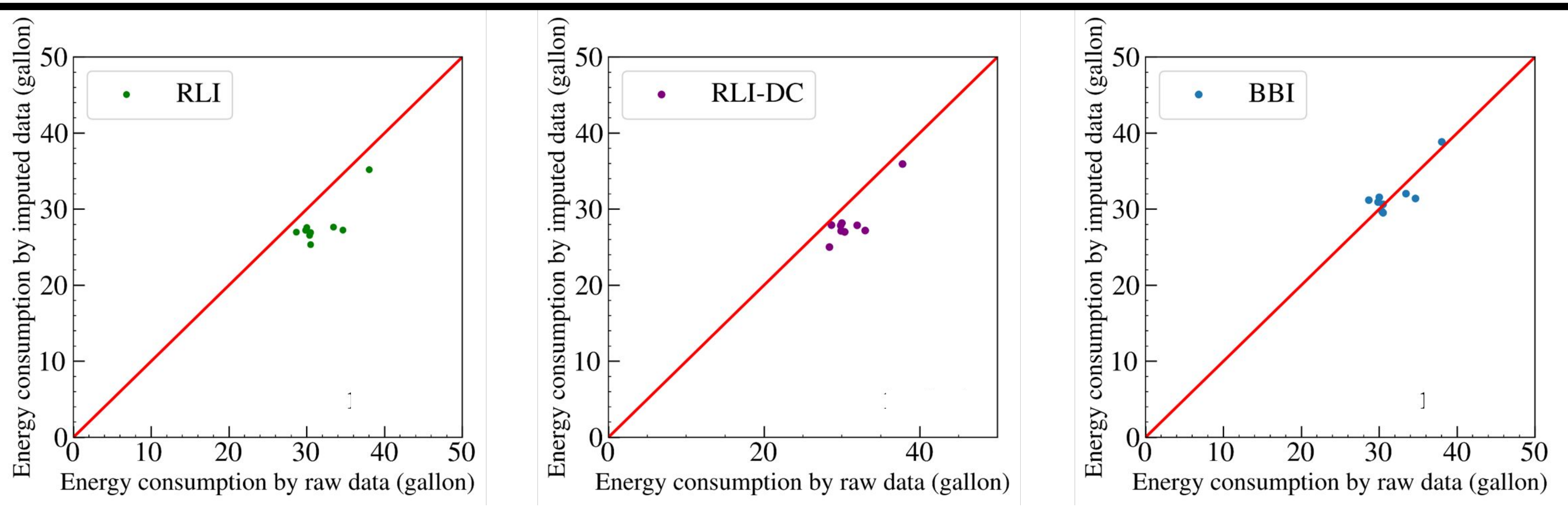
BBI

Fuel Consumption Comparison

- Fuel consumption estimation per minute



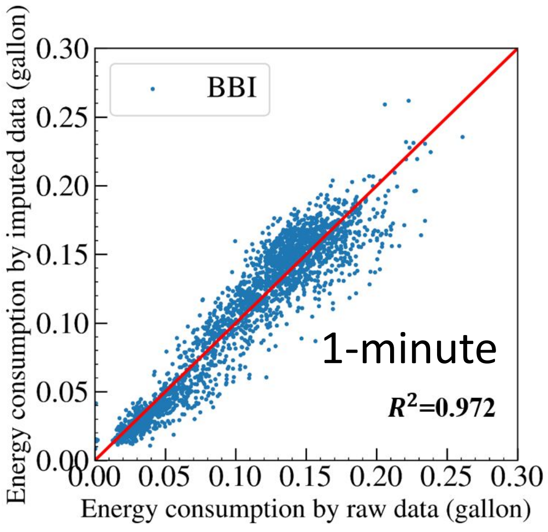
- Fuel consumption per route

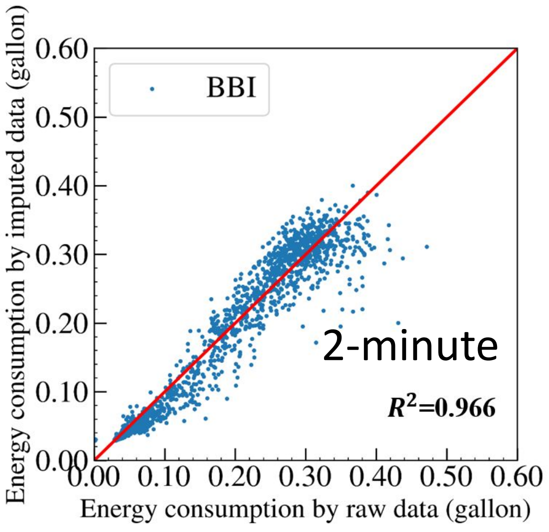


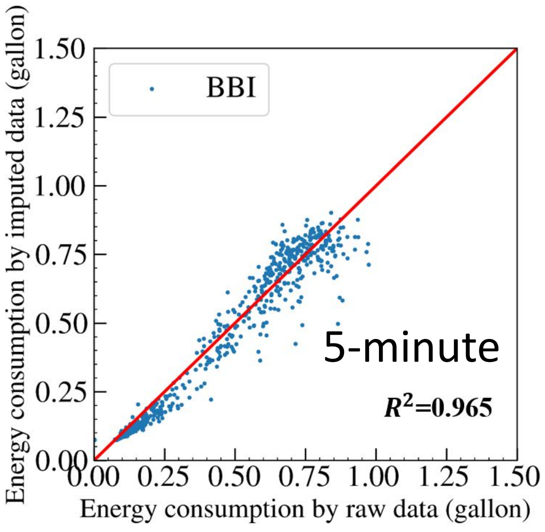
Barth, M., Younglove, T., Scora, G., 2005. Development of a heavy-duty diesel modal emissions and fuel consumption model.

Sensitivity Analysis

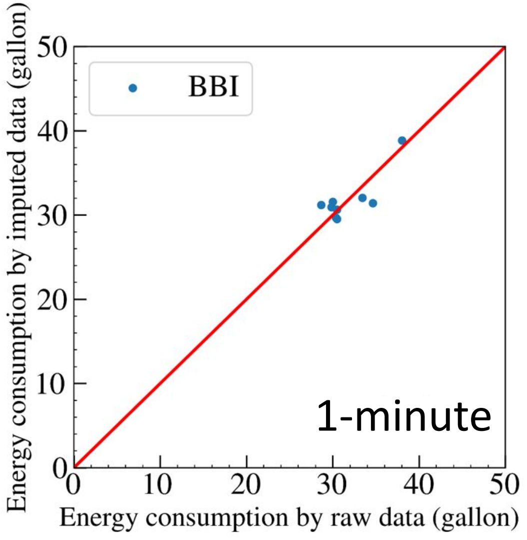
- Fuel consumption estimation by different time intervals

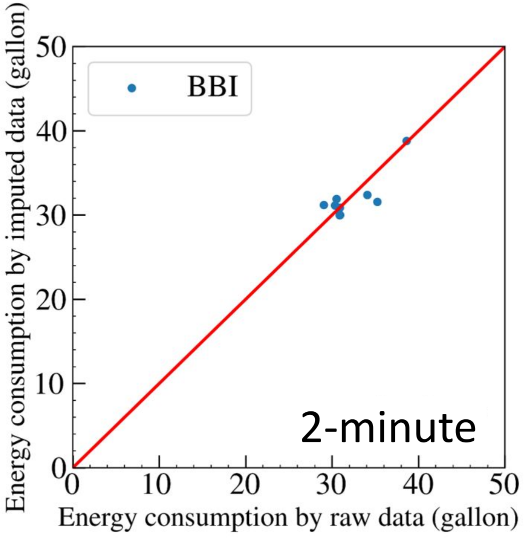


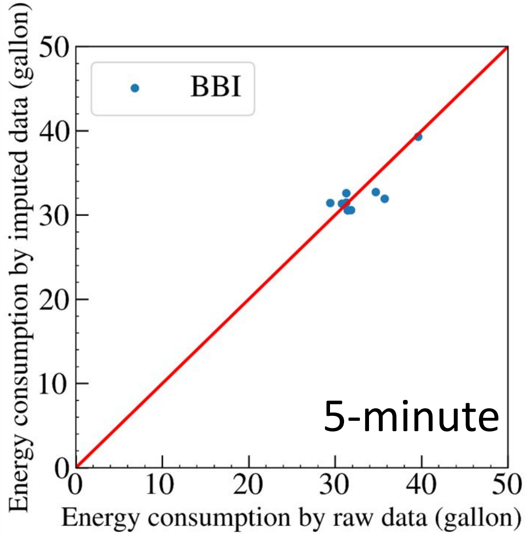




- Fuel consumption per route







Barth, M., Younglove, T., Scora, G., 2005. Development of a heavy-duty diesel modal emissions and fuel consumption model.

Estimation Accuracy

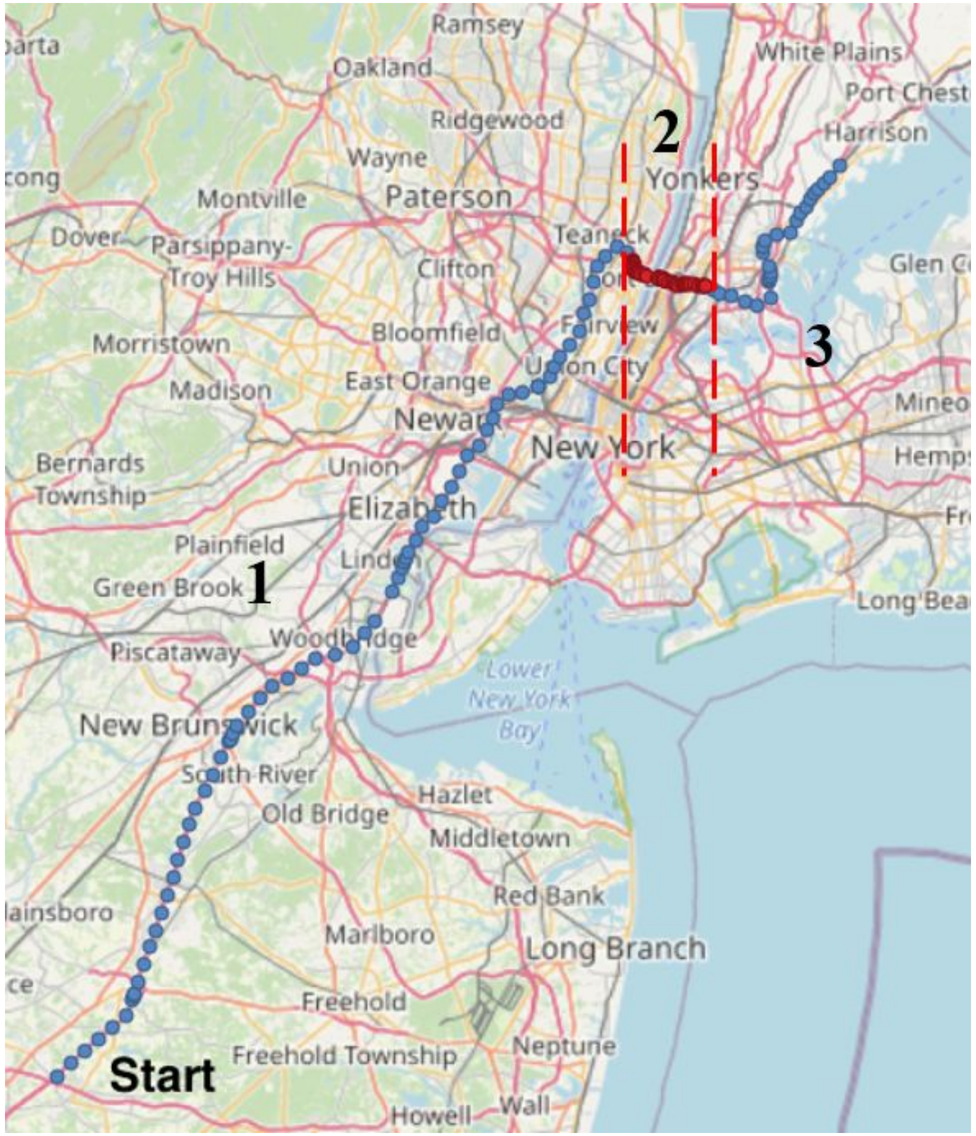
Mean Absolute Percent Error (MAPE) of Fuel consumption

MAPE	1-minute	2-minute	5-minute
RLI	10.19%	10.83%	11.94%
RLI-DC	7.11%	9.57%	10.71%
BBI	4.04%	4.11%	4.36%

Mean Absolute Percent Error (MAPE) of emissions estimation by EMFAC model

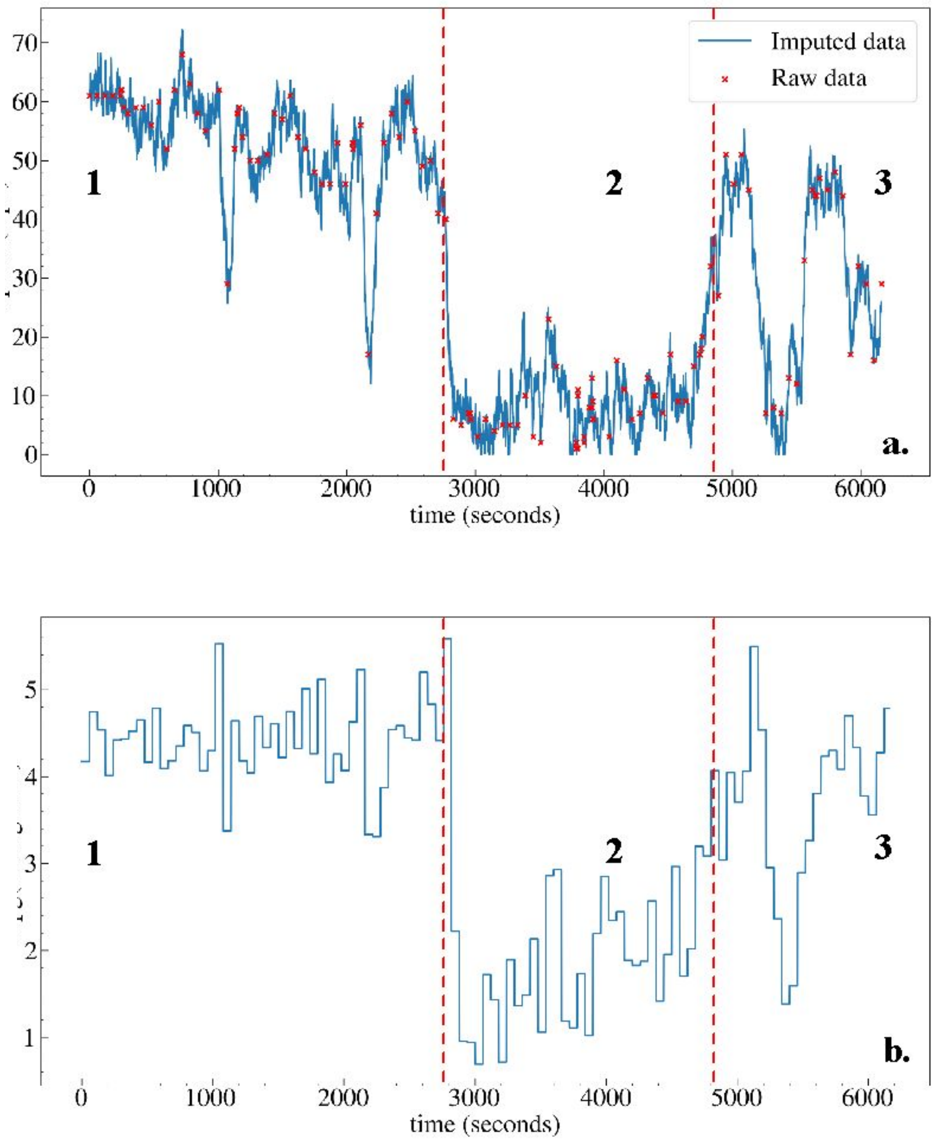
MAPE	CO_2	CO	NO_x	CH_4
RLI	1.44%	9.38%	5.82%	4.28%
RLI-DC	1.96%	9.82%	6.32%	4.99%
BBI	1.00%	6.83%	3.47%	3.44%

Application—Truck's Energy Efficiency

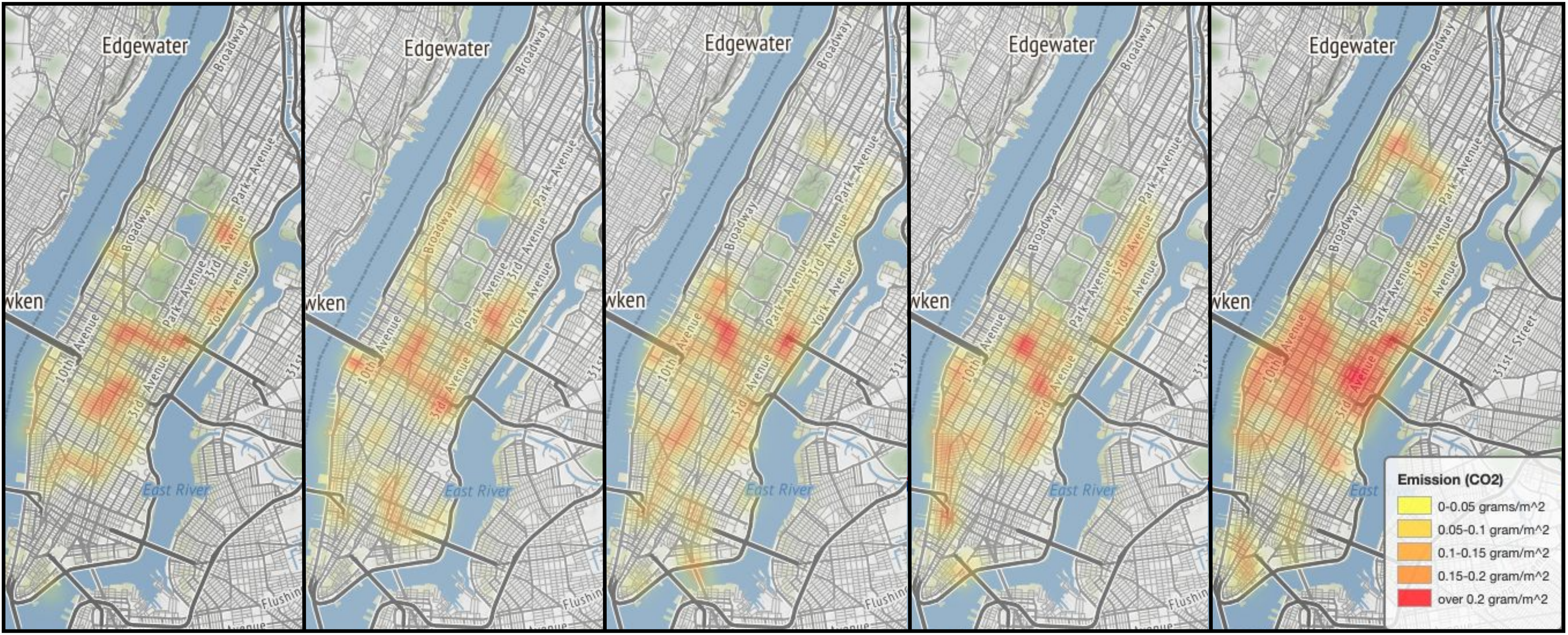


Speed (mph)

Fuel efficiency (miles/gallon)



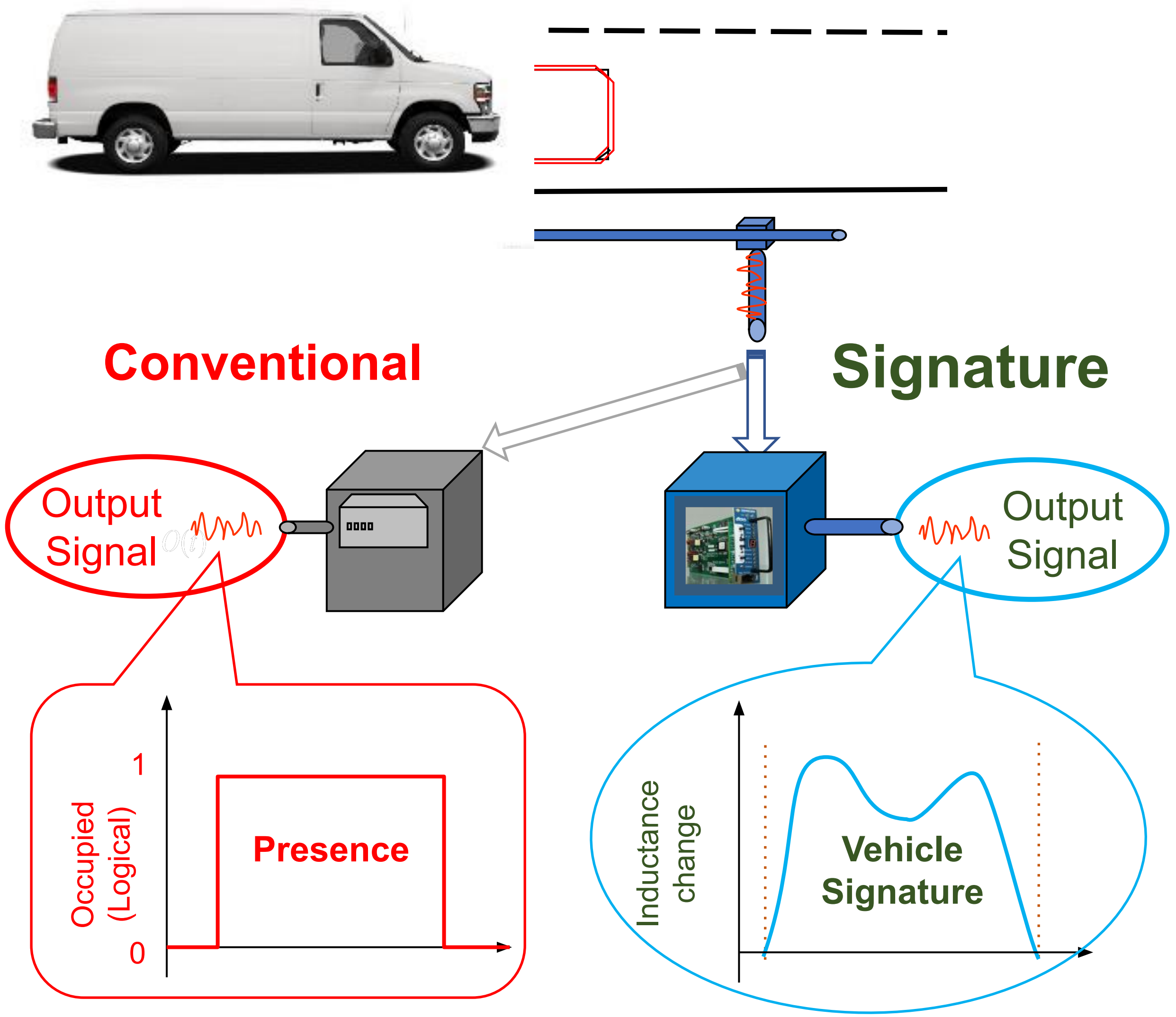
Application—Spatiotemporal Emission Changes

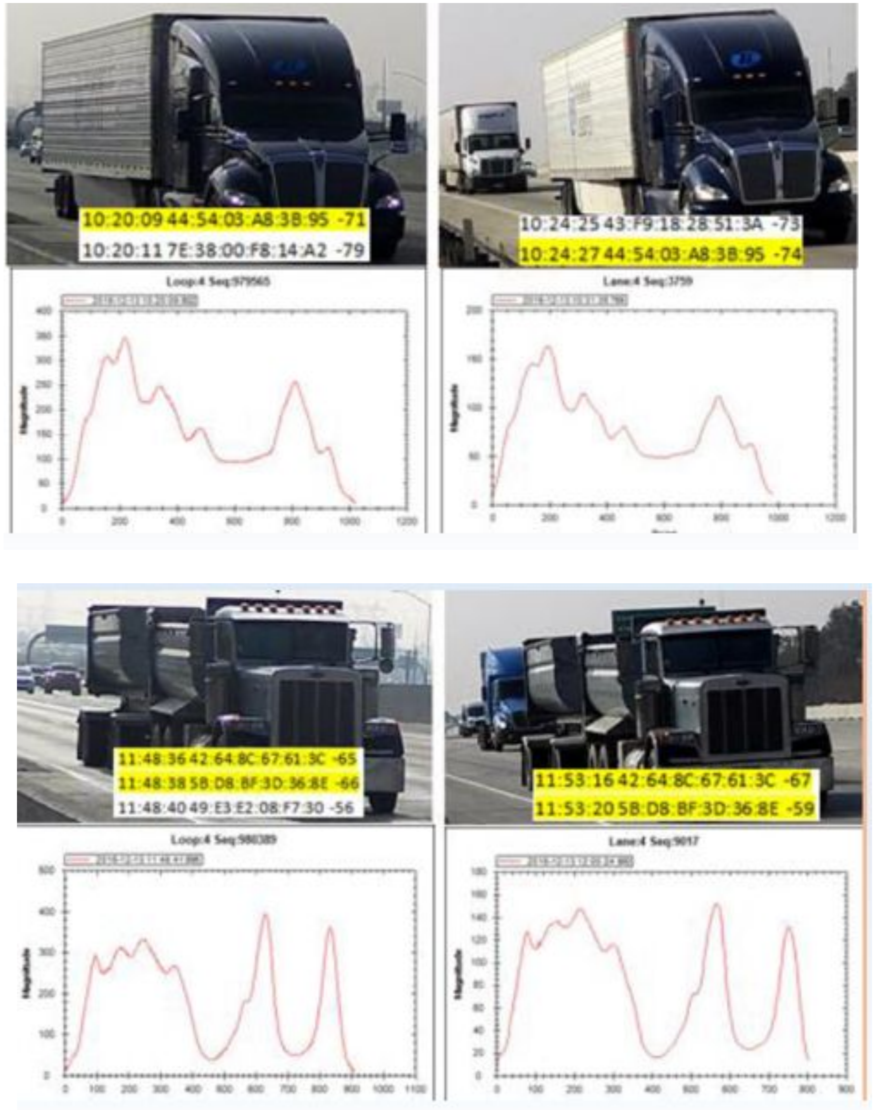


July 16 07:12-07:17 AM | 07:27-07:32 AM | 07:42-07:47 AM | 07:57-08:02 AM | 08:12-08:17 AM

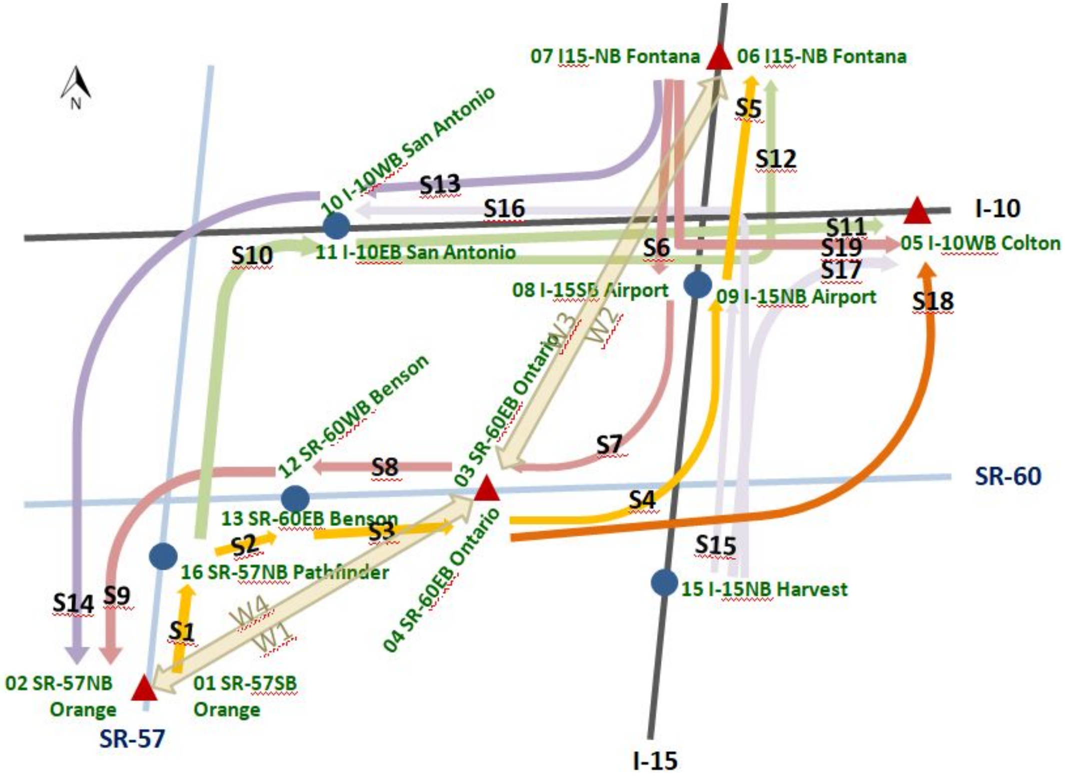
Data from Loop Detectors

Vehicle Classification and Re-Identification using Vehicle Signatures

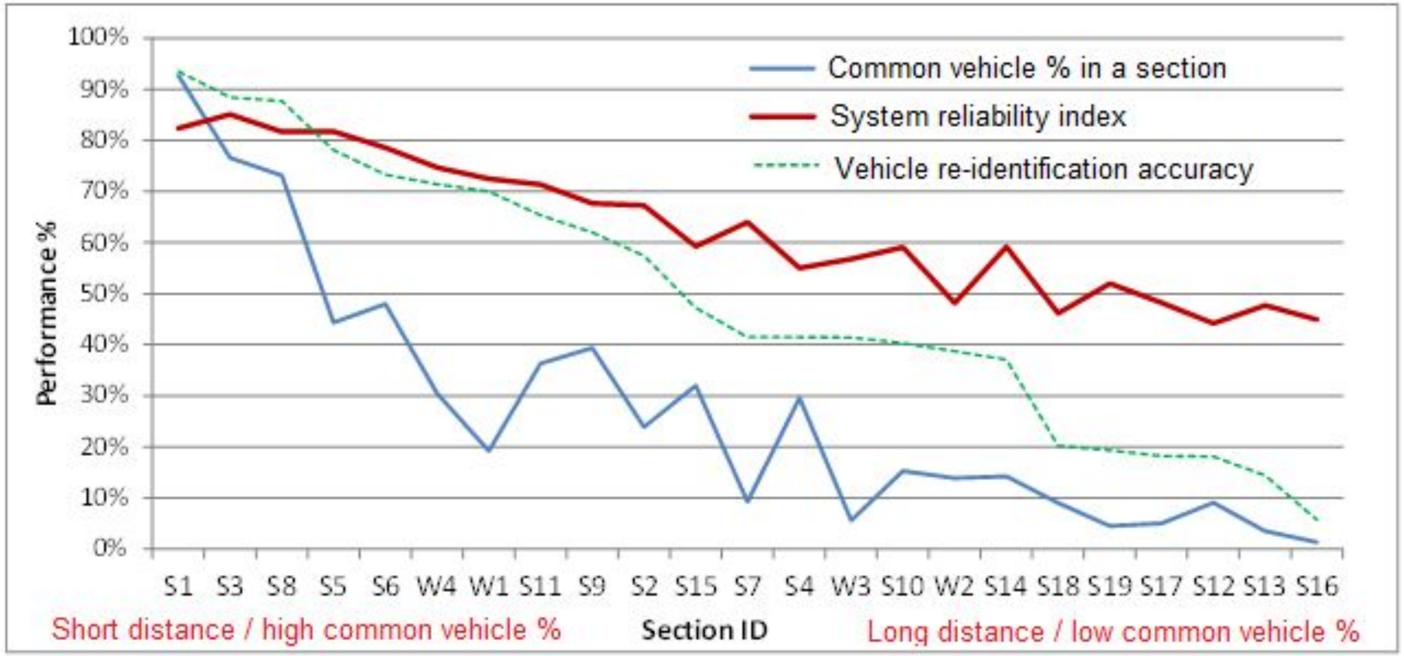


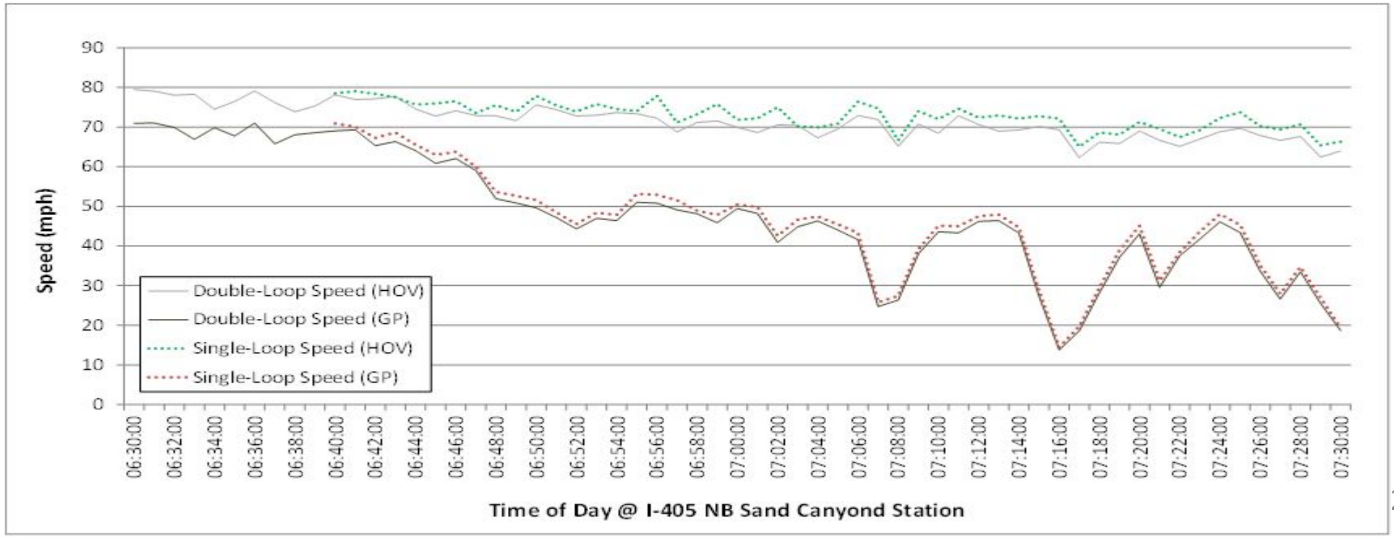


Vehicle Re-ID Performance

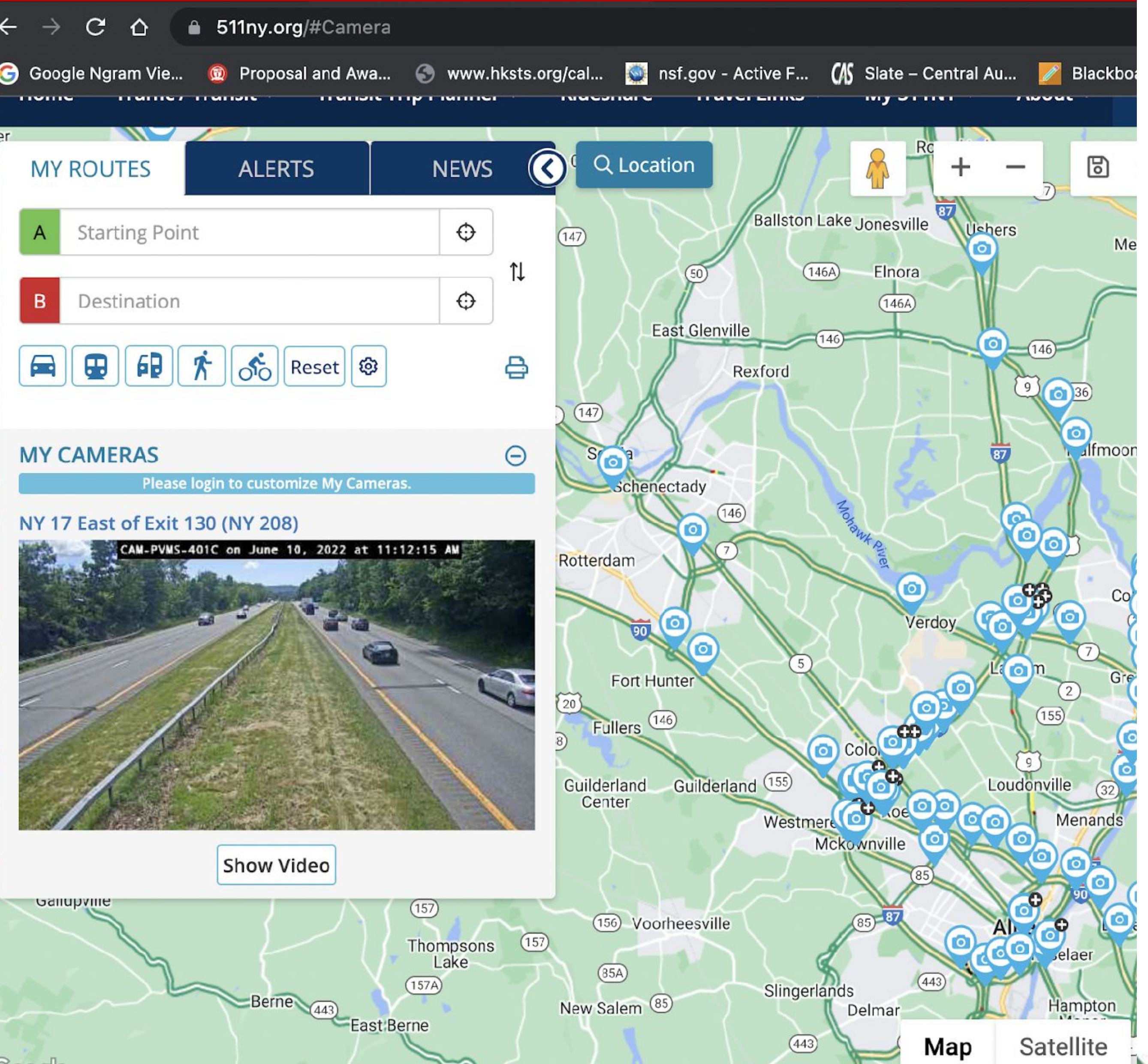


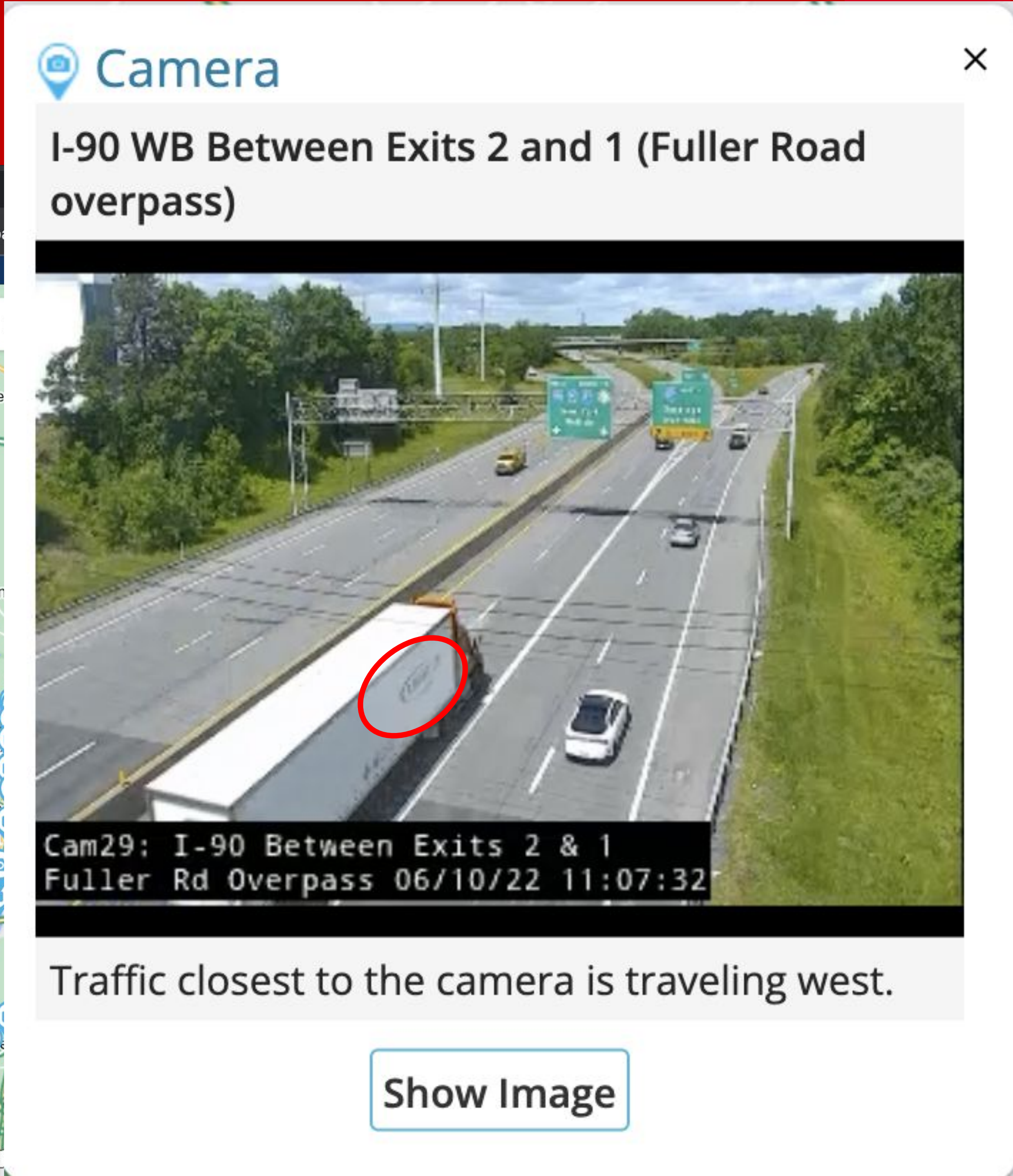
15 stations, 200 Square miles in southern CA



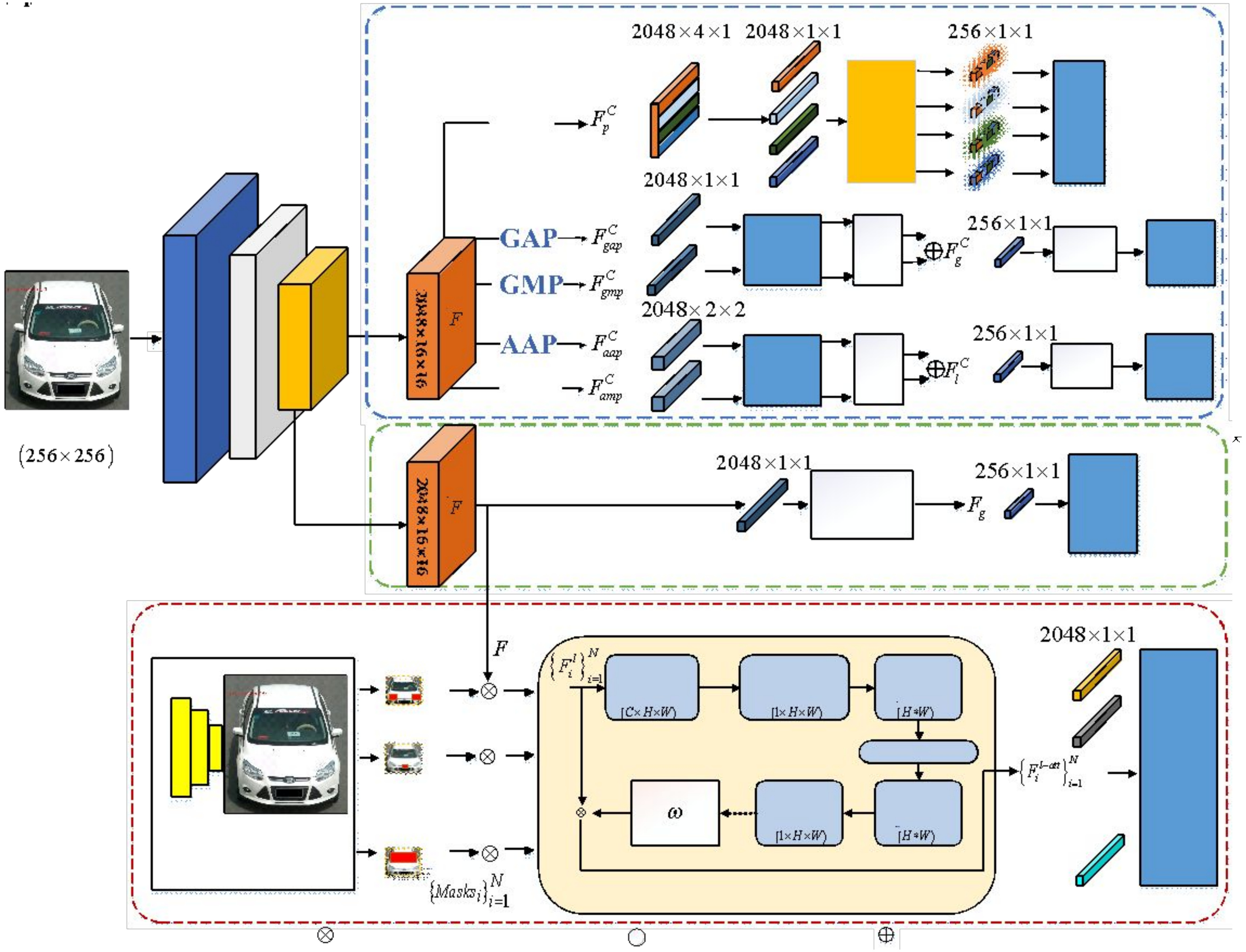


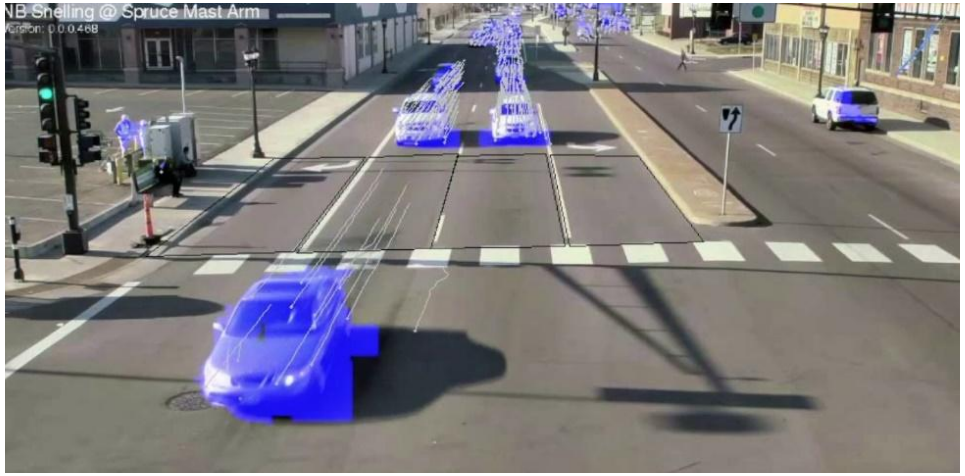
Data from Cameras





Few-Shot Learning for Vehicle Re-ID





Sun et al. (2022) Dual-Branch Network for Few-Shot Vehicle Re-ID with Enhanced Global and Local Features, in review

Conclusions

A simple but effective imputation technique for low-resolution speed data that:

- Provides accurate estimates of fuel consumption and emissions
- Does not require high volume data for model training
- Factors acceleration and travel distance constraints

Integrated with machine learning techniques for sparse data from

- Loop detectors using vehicle signatures
- Cameras using few-shot learning

Thank you!

hex6@rpi.edu

Sponsors and collaborators:

National Science Foundation
WHERE DISCOVERIES BEGIN

U.S. DEPARTMENT OF ENERGY

VREF CENTER OF EXCELLENCE FOR SUSTAINABLE URBAN FREIGHT SYSTEMS

CLR Analytics
INNOVATIVE TRANSPORTATION SOLUTIONS