

Machine Learning for Activity-Based Road Transportation Emissions Estimation

Tackling Climate Change with ML Workshop at NeurIPS 2022

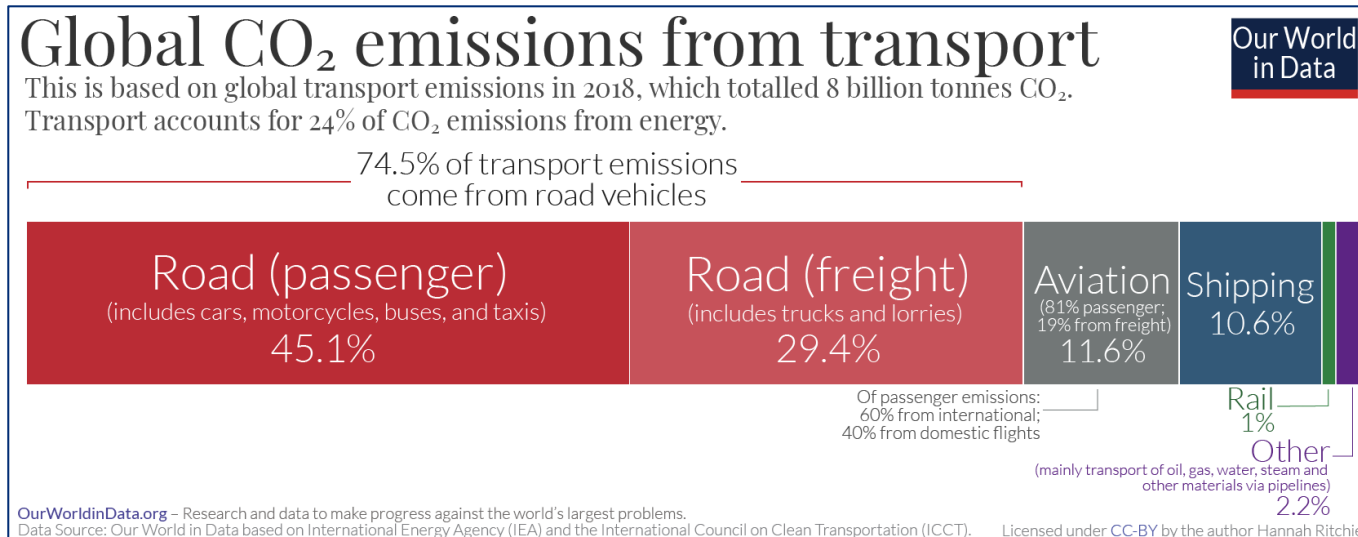
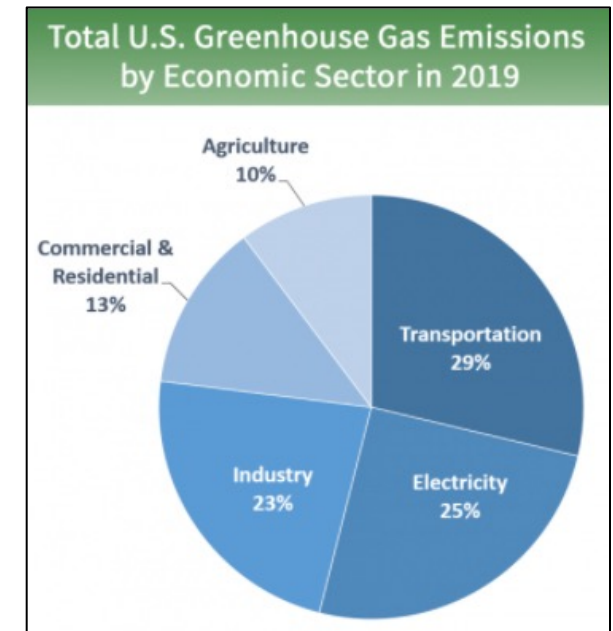
Derek Rollend, Kevin Foster, Tomek Kott, Rohita Mocharla
Rai Muñoz, Neil Fendley, Chace Ashcraft, Frank Willard, Marisa Hughes

The Johns Hopkins University Applied Physics Laboratory

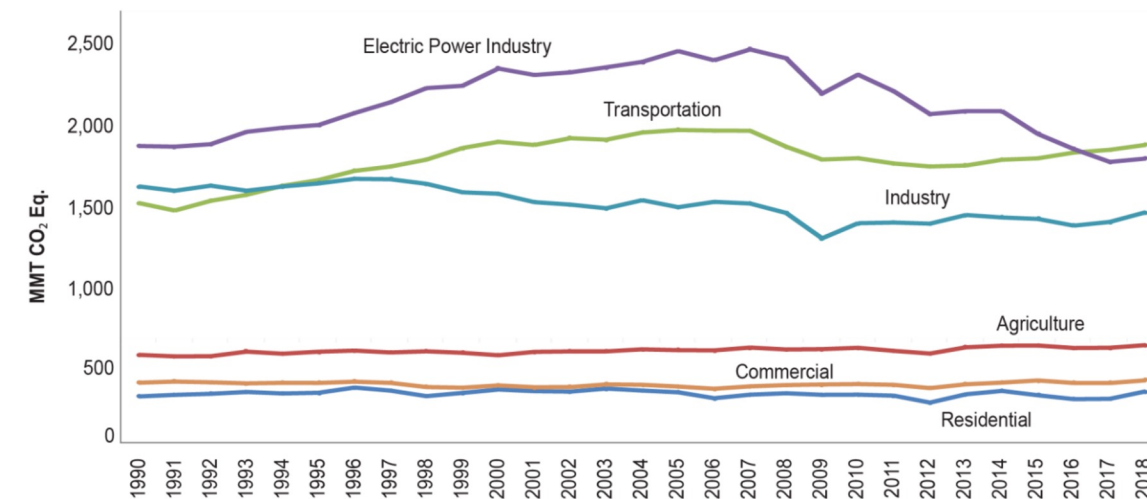
Contact: derek.rollend@jhuapl.edu

Motivation

- Transportation is **one of the largest sectors** of greenhouse gas emissions
 - 27% of all U.S. GHG emissions in 2020 [1]
 - 12.6% of global GHG emissions in 2019 [2]
- **Goal:** independently estimate road transportation emissions at a global scale (e.g., using AI/ML, satellite imagery, and other widely available data sources)



U.S. Greenhouse Gas Emissions Allocated to Economic Sectors*



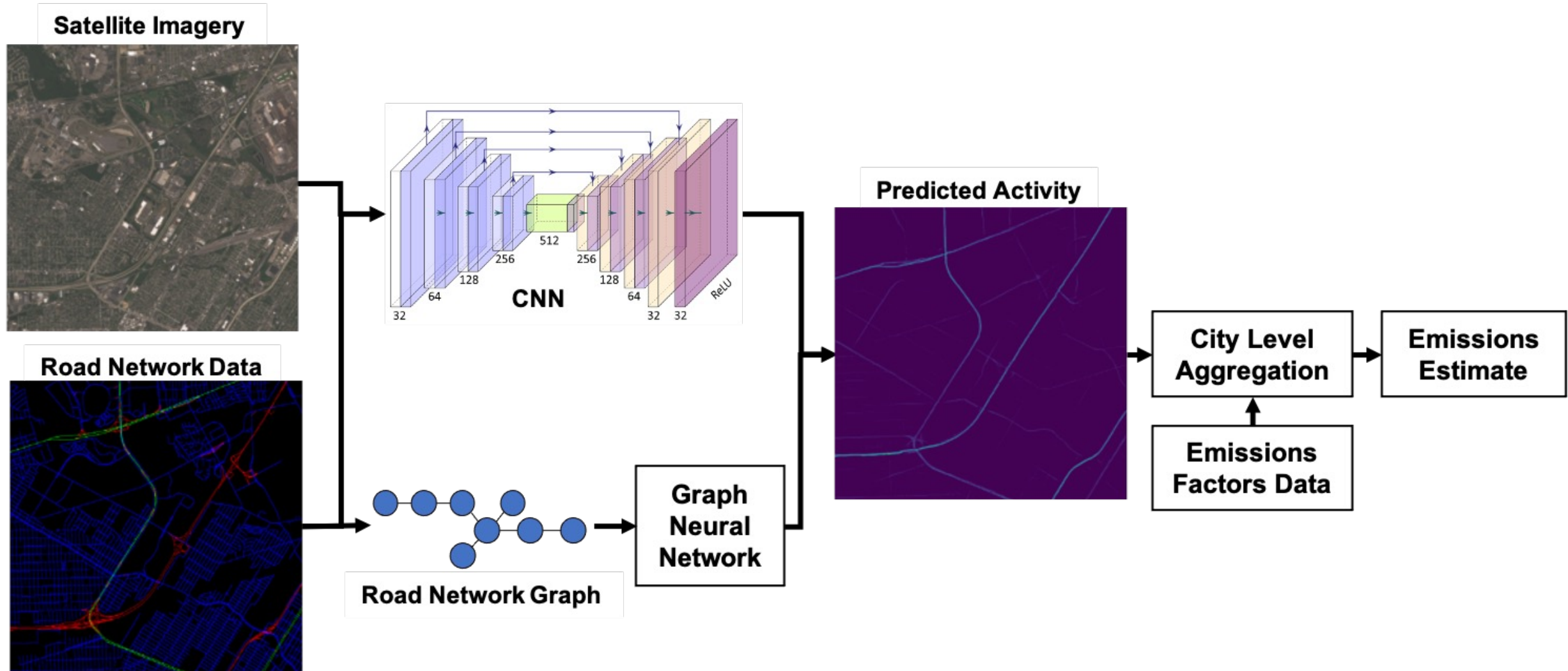
*Land use sinks and U.S. territories are excluded from this figure.

<https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks-1990-2018>

Approach

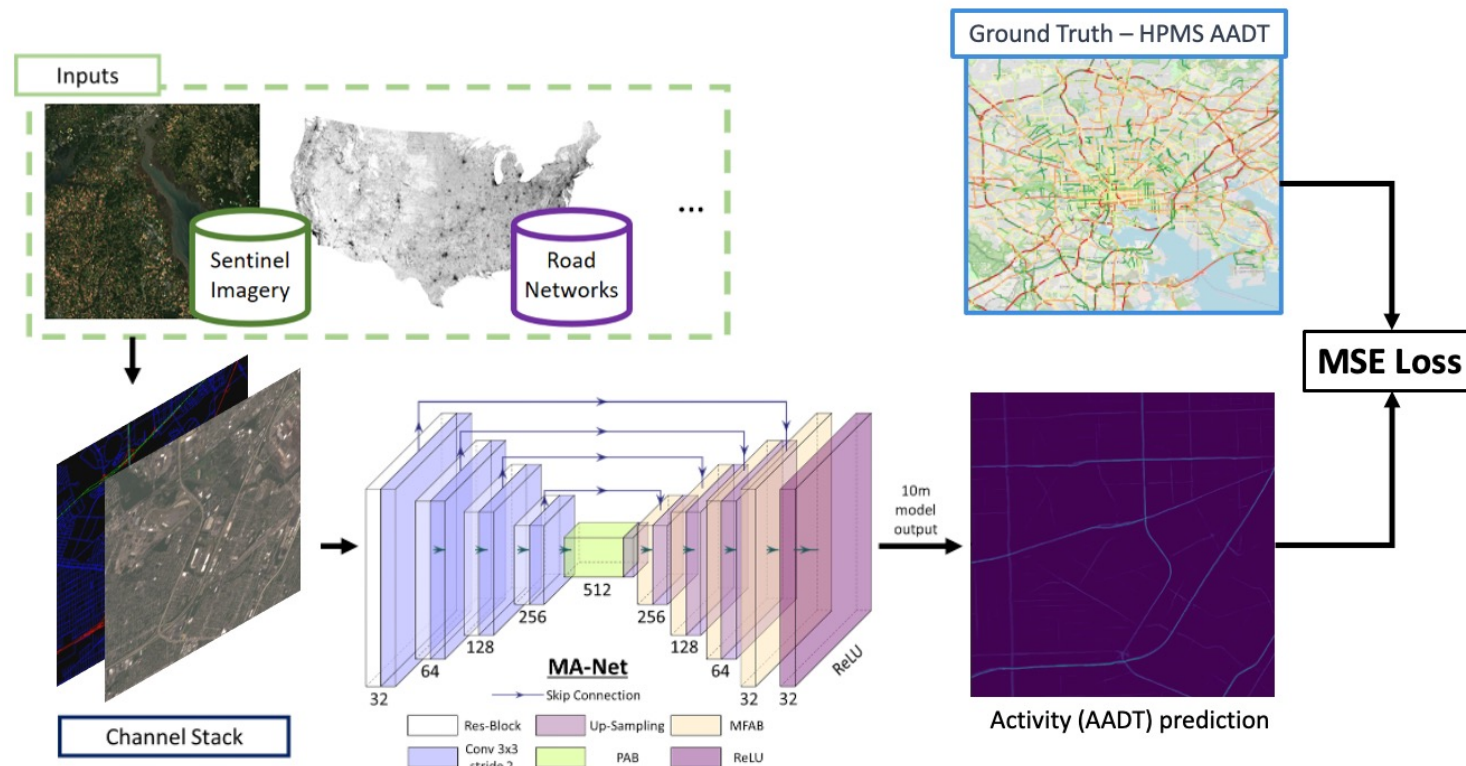


Machine Learning Approach



Data & Model Training

- Ground truth data: U.S. Highway Performance Monitoring System Average Annual Daily Traffic (AADT) data set from 2017 [3]
- OpenStreetMap (OSM) [4] road network data used for both CNN and GNN models
- **CNN models:** Sentinel-2 [5] or PlanetScope [6] satellite imagery used in combination with OSM
- **GNN models:** Graph attention network v2 (GATv2) [7] architecture



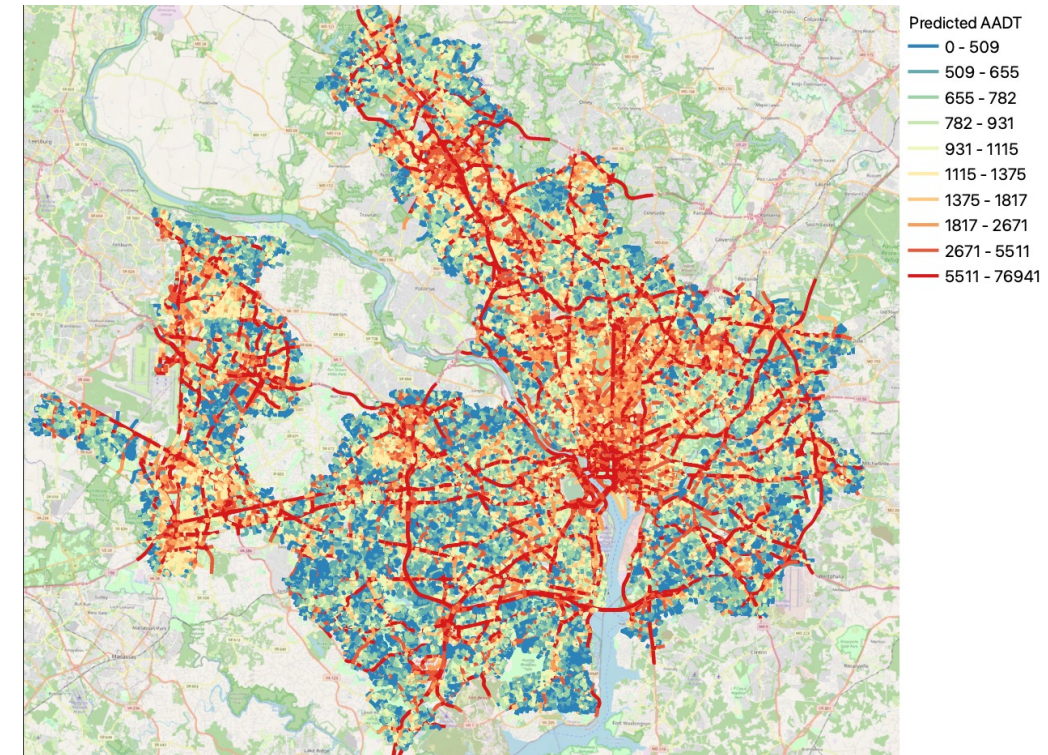
AADT Validation

AADT error metrics for 14 U.S. hold out cities. RMSE is in units of vehicles per day.

Method	RMSE	MAPE	MPE	Pearson's ρ
S2+OSM	4823.6	116.3%	-39.3%	0.58
S2+OSM Ensemble	5249.5	102.3%	-71.74%	0.58
Planet+OSM	3329.9	159.9%	41.01%	0.60
GNN OSM	4470.0	137.6%	103.3%	0.87
GNN OSM+GHSL	4384.9	143.3%	110.6%	0.87
GNN OSM+CNN	4415.3	135.0%	99.27%	0.88
GNN OSM Ensemble	4307.3	142.3%	113.0%	0.88

AADT error metrics for international cities: 26 cities in the UK [8], Buenos Aires [9], and Paris [10]. RMSE is in units of vehicles per day.

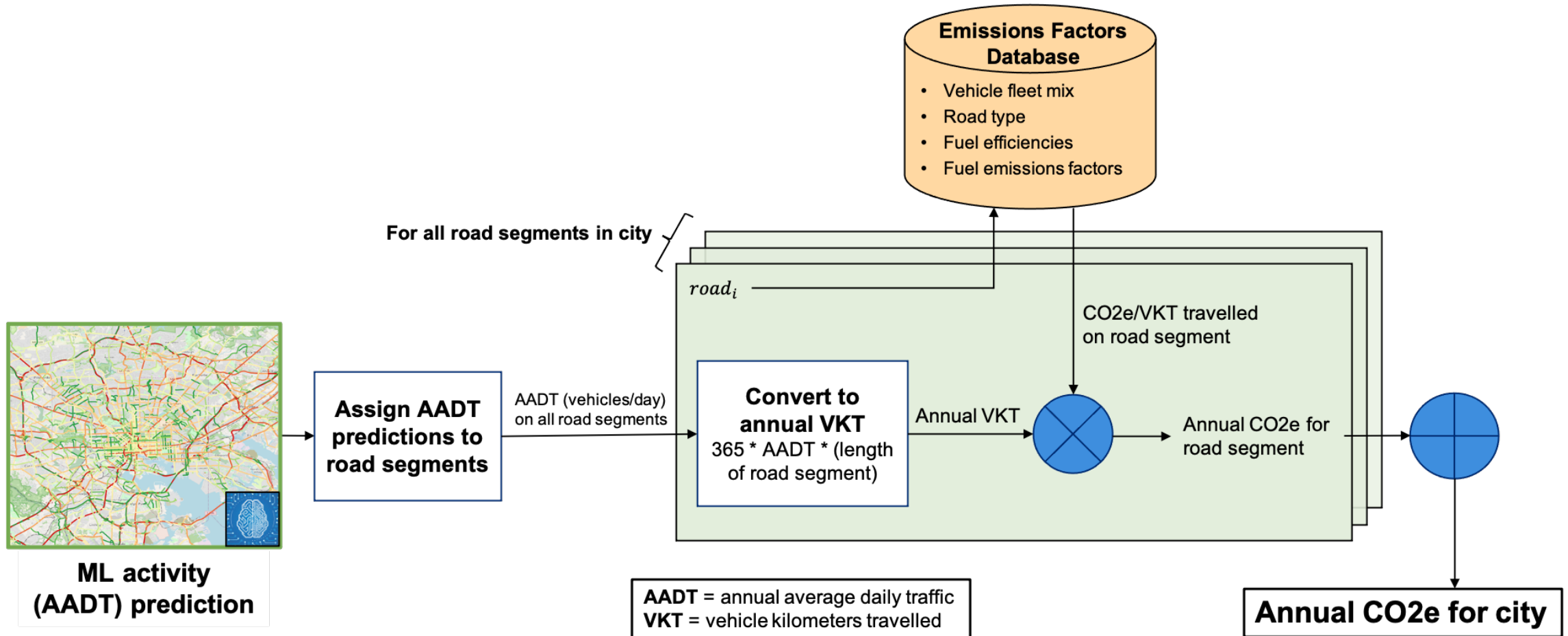
Region	RMSE	MAPE	MPE	Pearson's ρ
U.K. 26 (2018)	3804.6	119.5%	49.2%	0.69
U.K. 26 (2019)	3177.2	130.9%	63.0%	0.73
U.K. 26 (2020)	3447.0	84.7%	20.6%	0.69
Buenos Aires (2017)	8750.2	74.3%	71.8%	0.66
Paris (2021)	9467.9	96.3%	20.4%	0.79



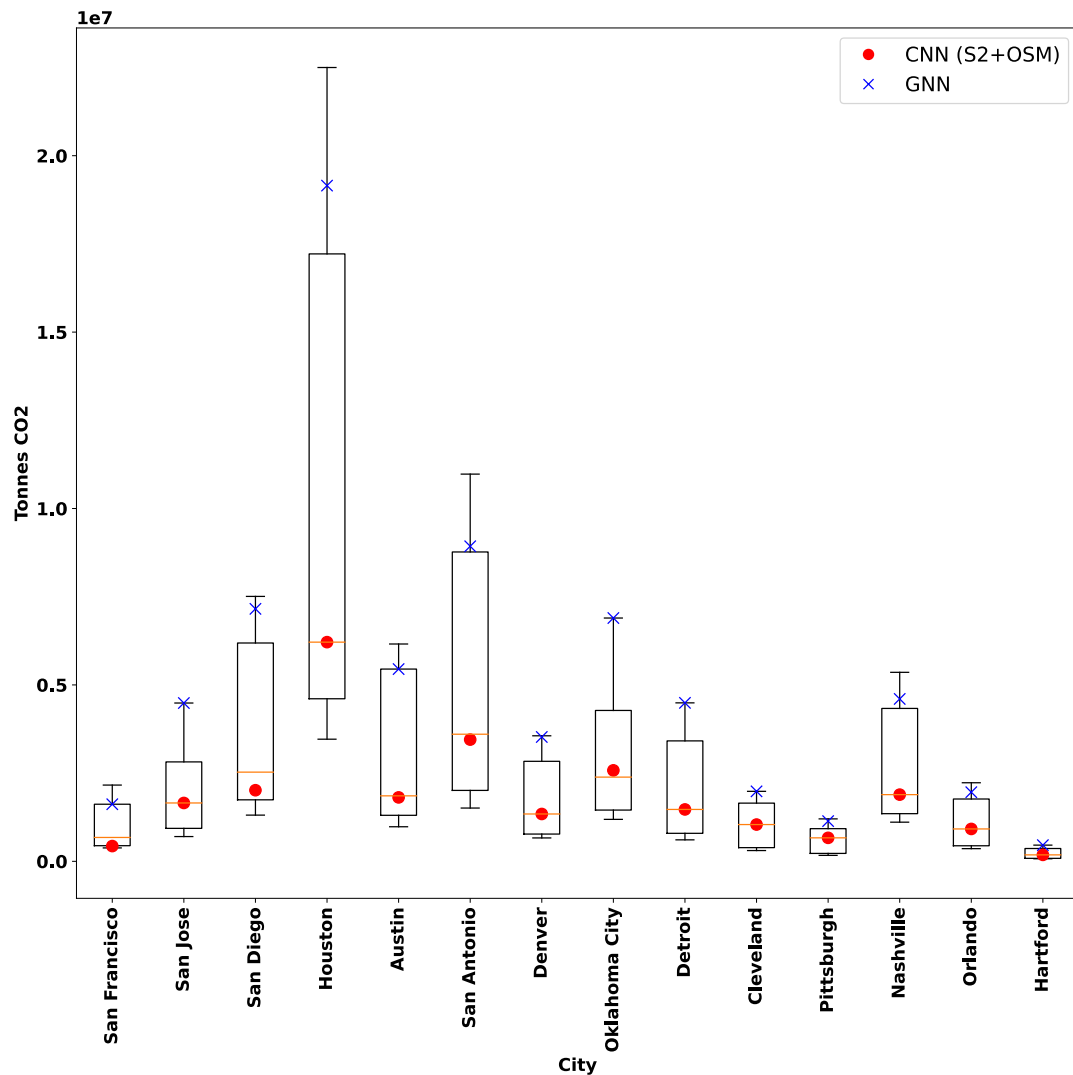
Example ensembled AADT predictions for the greater Washington D.C. area

Activity to Emissions

Leverage **region-specific** emissions factors data to translate ML-predicted activity to total emissions.



U.S. Emissions Validation

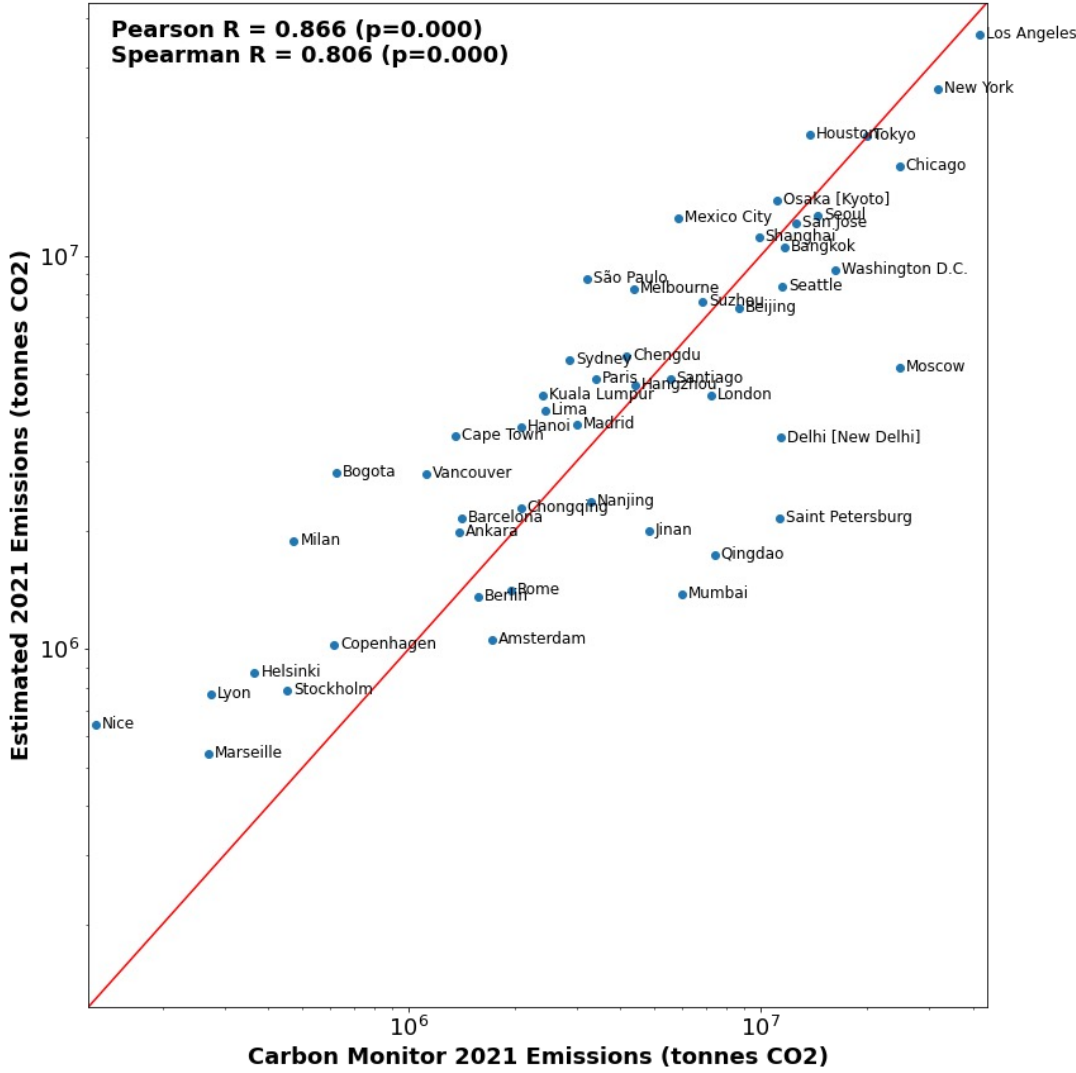


- Emissions estimates compared against other major emissions inventories [11,12,13] for 14 hold out U.S. cities
- Strong correlation** between our estimates and others
- Range of values highlights **uncertainties** and **discrepancies** between various methods

Emissions Dataset	CNN				GNN			
	RMSE	Mean Error	MAPE	ρ	RMSE	Mean Error	MAPE	ρ
EIE_v1_2018	544,225	407,997	77.3%	0.94	3,706,827	3,706,827	321.5%	0.95
EIE_v2_2018	1,180,437	-1,153,065	36.1%	0.94	2,223,303	2,145,764	71.3%	0.96
DARTE_2015	2,606,389	-2,606,389	53.6%	0.98	708,514	692,440	19.8%	0.99
DARTE_2017	3,505,472	-3,505,472	59.5%	0.98	875,254	-206,642	17.2%	0.99
VULCAN_lo_2015	912,134	912,134	124.8%	0.98	4,210,964	4,210,964	473.2%	0.99
VULCAN_mn_2015	761,213	759,672	93.3%	0.98	4,058,502	4,058,502	391.8%	0.99
VULCAN_hi_2015	617,740	607,210	71%	0.98	3,906,040	3,906,040	330.7%	0.99

MAE and Mean Error are in units of tonnes CO₂

Global Emissions Validation



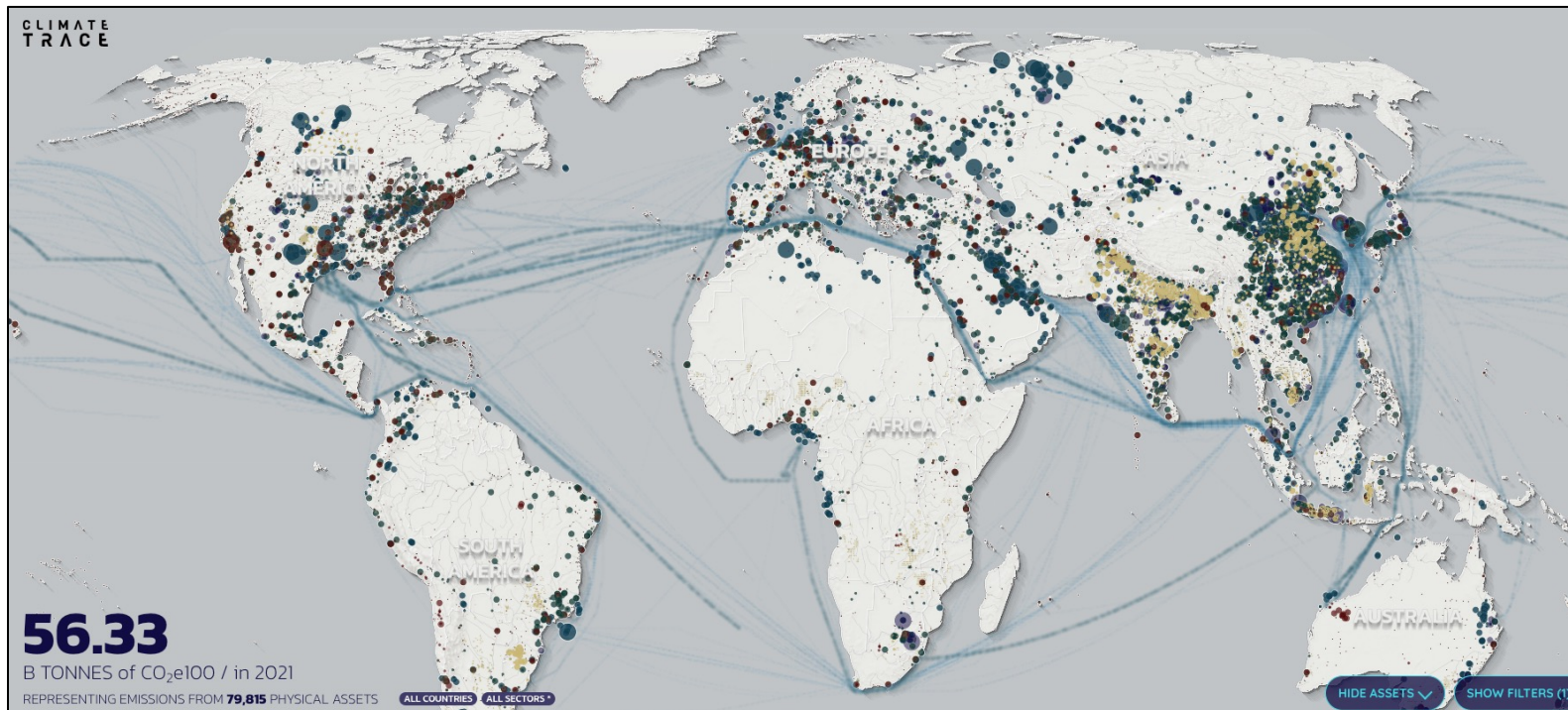
- Emissions estimates compared against other global emissions inventories [14,15] for 14 hold out U.S. cities
- **Strong correlation** between our estimates and others
- **Discrepancies** between estimates warrants future investigation

Emissions Dataset	# of Cities	MAE	MAPE	Mean Error	MPE	Pearson's ρ
EDGAR 2015	500	1,158,740	68.80%	248,624	23.60%	0.74
Carbon Monitor 2019	50	2,857,690	72.40%	-844,634	44.40%	0.87
Carbon Monitor 2020	50	2,634,598	83.20%	-317,283	55.70%	0.86
Carbon Monitor 2021	50	2,795,294	73.50%	-781,053	42.40%	0.87

MAE and Mean Error are in units of tonnes CO₂

Discussion and Next Steps

- Hybrid ML + emissions factors method for global road transportation emissions estimation
- Validation performed for both ML activity predictions and derived emission estimates, both within the U.S. and for global cities.
- Plan to explore integration of traffic/mobility data to improve temporal resolution
- Emissions estimates for top 500 global cities included in November 2022 Climate TRACE asset-level release (www.climate TRACE.org)



Contact: derek.rollend@jhuapl.edu

References

1. Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2020. Tech. rep. U.S. Environmental Protection Agency, 2022.
2. World Resource Institute. *Climate Watch Historical GHG Emissions*. <https://www.climatewatchdata.org/ghg-emissions>. 2022.
3. US Federal Highway Administration. *Highway Performance Monitoring System (HPMS) Data*. 2017. URL: <https://www.fhwa.dot.gov/policyinformation/hpms>.
4. Mordechai Haklay and Patrick Weber. “OpenStreetMap: User-Generated Street Maps”. In: *IEEE Pervasive Computing* (2008).
5. Matthias Drusch et al. “Sentinel-2: ESA’s optical high-resolution mission for GMES operational services”. In: *Remote sensing of Environment* (2012).
6. Planet Labs Inc. *Planet imagery product specifications*. 2022. URL: https://assets.planet.com/docs/Planet_Combined_Imagery_Product_Specs_letter_screen.pdf (visited on 09/13/2022).
7. Shaked Brody, Uri Alon, and Eran Yahav. *How Attentive are Graph Attention Networks?* 2021. DOI: 10.48550/ARXIV.2105.14491. URL: <https://arxiv.org/abs/2105.14491>.
8. Department for Transport. *Road Traffic Statistics*. 2020. URL: <https://roadtraffic.dft.gov.uk>.
9. Ministry of Transport - National Directorate of Roads. *2017 TMDA data*. 2017. URL: <https://datos.transporte.gob.ar/dataset/tmda>.
10. Department of Roads and Travel - Service des Déplacements - Poste Central d’Exploitation Lutèce. *Road counting - Traffic data from permanent sensors*. 2021. URL: <https://parisdata.opendatasoft.com/explore/dataset/comptages-routiers-permanents>.
11. Google. *Environmental Insights Explorer (EIE)*. 2022. URL: <https://insights.sustainability.google>.
12. C. Gately, L.R. Hutya, and I.S. Wing. *DARTE Annual On-road CO2 Emissions on a 1-km Grid, Conterminous USA V2, 1980-2017*. en. 2019. DOI: 10.3334/ORNLDAAAC/1735. URL: https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1735.
13. Kevin R Gurney et al. “The Vulcan version 3.0 high-resolution fossil fuel CO2 emissions for the United States”. In: *Journal of Geophysical Research: Atmospheres* (2020).
14. Greet Janssens-Maenhout et al. “EDGAR v4.3.2 Global Atlas of the three major Greenhouse Gas Emissions for the period 1970–2012”. In: *Earth System Science Data Discussions* (2017).
15. Zhu Liu et al. “Carbon Monitor, a near-real-time daily dataset of global CO2 emission from fossil fuel and cement production”. In: *Scientific Data* 7 (Nov. 2020). DOI: 10.1038/s41597-020-00708-7



JOHNS HOPKINS
APPLIED PHYSICS LABORATORY