Tracking Greenhouse Gas Emissions

Estimating and Controlling Transportation Emissions

Assignments

Brightspace discussion question:

“Which do you think plays a bigger role in driving greenhouse gas reductions: government or companies? Why?”

Due this Friday by 5pm.

Second programming assignment on predicting building energy use

Due Friday the 17th by midnight.

Climate change in the news

Climate change in the news

New York

Uber and Lyft in New York required to be zero-emission by 2030, officials say

Mayor Eric Adams announced the initiative was part of the 'Working People's Agenda' at his second state of the city address

Gloria Oladipo
@gaoladipo
Fri 27 Jan 2023 01.00 EST

Uber and Lyft both shared statements indicating support for the coming change, the Verge reported. Photograph: Robyn Beck/AFP/Getty Images

Uber and Lyft vehicles in New York City will be required to be zero-emission by 2030, New York officials announced on Thursday.

The decision could affect the 100,000 for-hire vehicles operating throughout New York.

New York's mayor, Eric Adams, announced the initiative as part of his "Working People's Agenda" while giving his second state of the city address, according to a city press release.

"Today, we are announcing that Uber and Lyft will be required to have a zero-emissions fleet by 2030. That's zero emissions for over 100,000 vehicles on our city streets," announced Adams, adding that Uber and Lyft support the transition and that the shift will come at no additional cost to drivers.

"We're also encouraging New Yorkers who drive to make the switch to electric vehicles as well, adding charging stations in all five boroughs."

Uber and Lyft have already announced their own goals when it comes to having 100% electric vehicle fleets by 2030, reported Bloomberg News.

Both companies have attempted to entice drivers to trade in emitting cars for electric vehicles using perks and incentives.

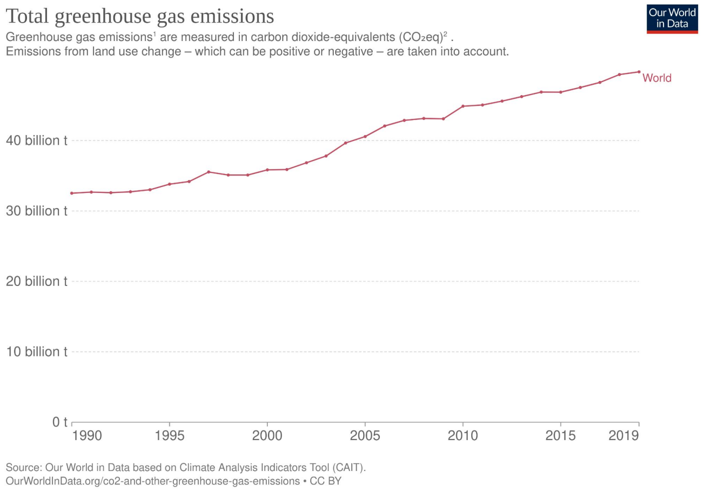
Uber is offering drivers who use an electric vehicle an extra $1 earned for their ride and partnered with car rental company Hertz to offer electric vehicle rental opportunities.

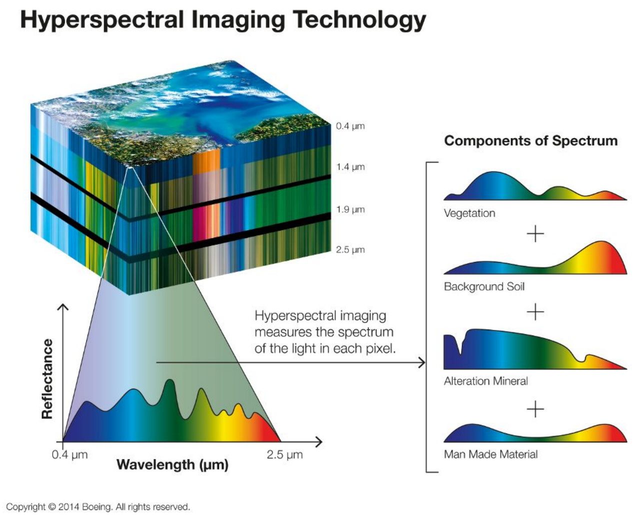
Lyft has offered similar promotions and promised to expand electric vehicle rental opportunities for drivers who are not able to purchase a new car.

But only 1% of ride share drivers in New York use electric vehicles as of September, reported Bloomberg.

California passed similar rules that would require ride share drivers to use electric vehicles by 2030.

Recap

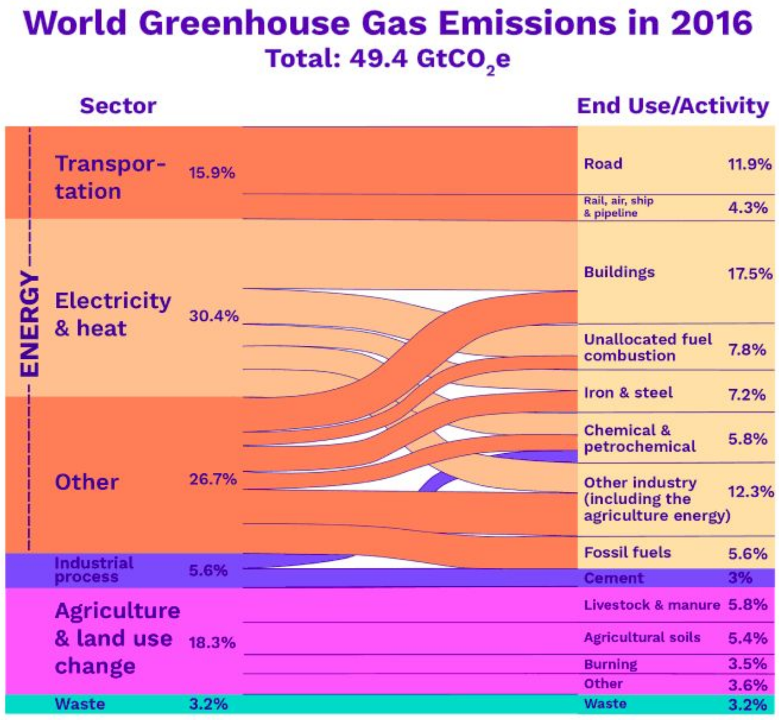




2006 IPCC Guidelines for National Greenhouse Gas Inventories

Detecting Methane Plumes using PRISMA: Deep Learning Model and Data Augmentation

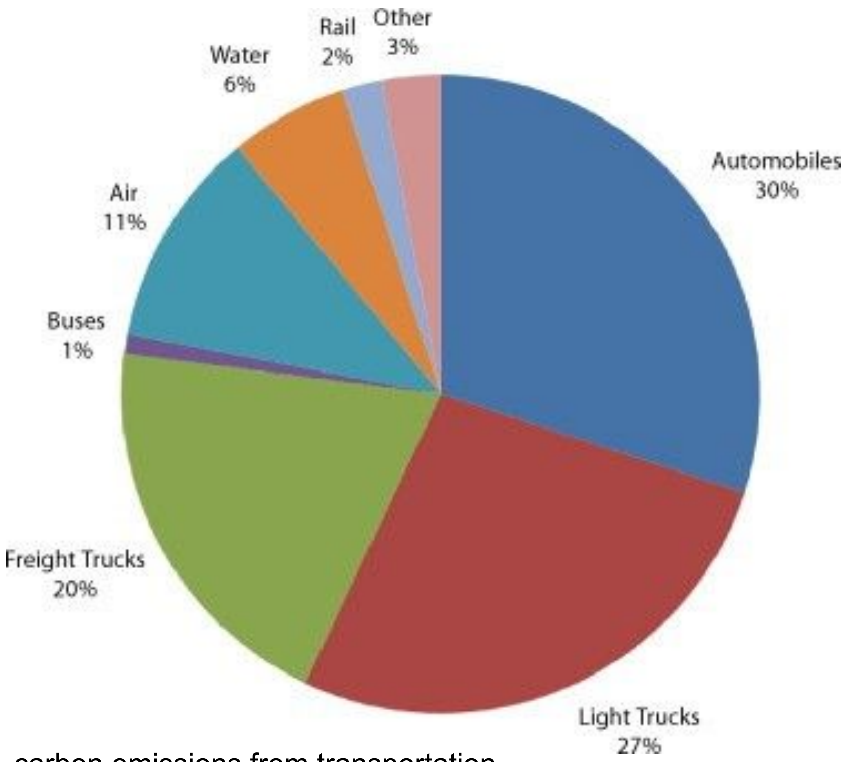
Transportation emissions make up 16% of global total



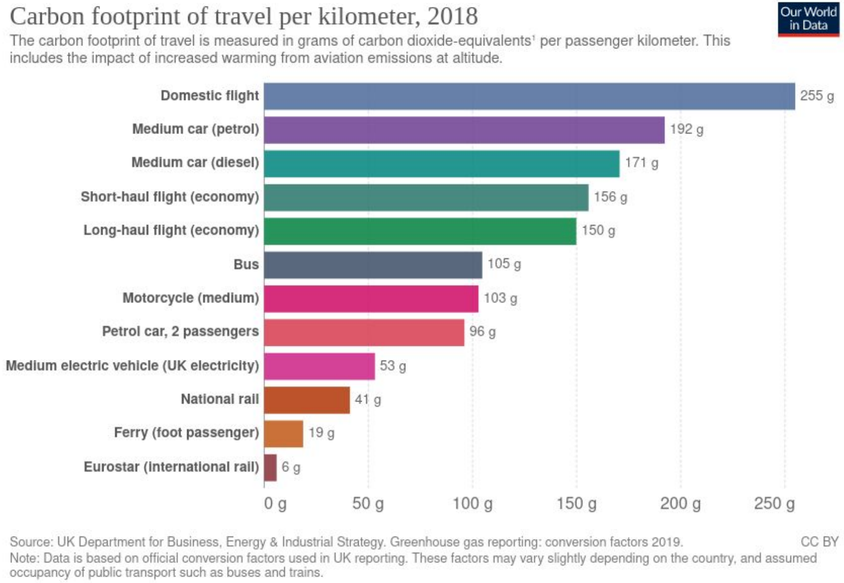
Source: Greenhouse gas emissions on Climate Watch. Available at: https://www.climatewatchdata.org

Breakdown of U.S. transport emissions

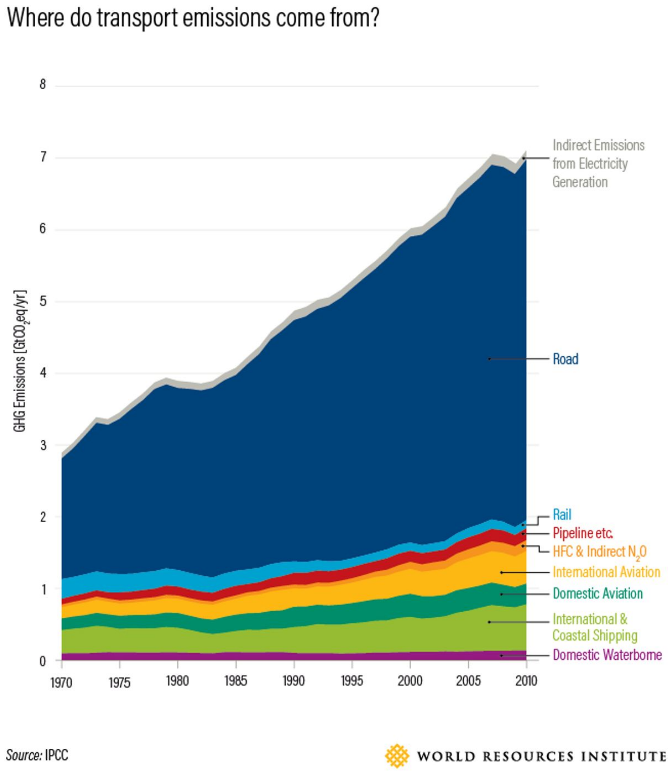
The largest sector contributing to transportation emissions is personal car use. Aviation is the worst per distance emitter.

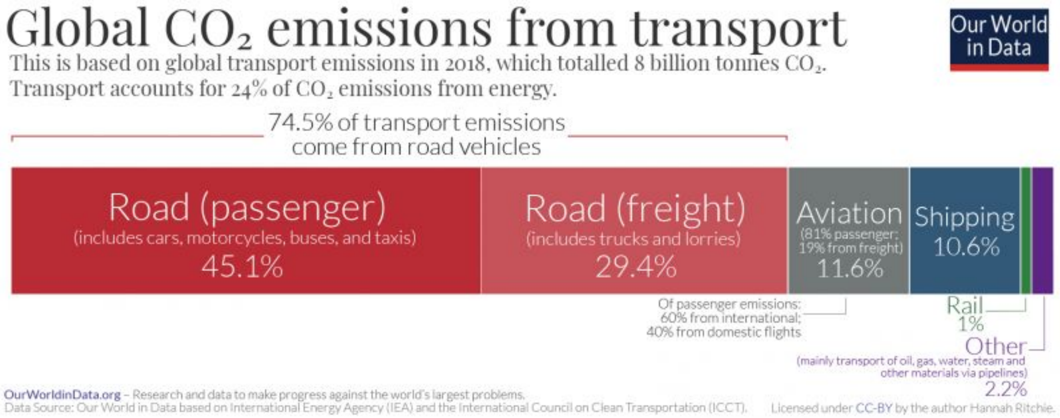


U.S. carbon emissions from transportation, 2005 (*Source*: EIA, 2007b).



Breakdown of global transport emissions over time





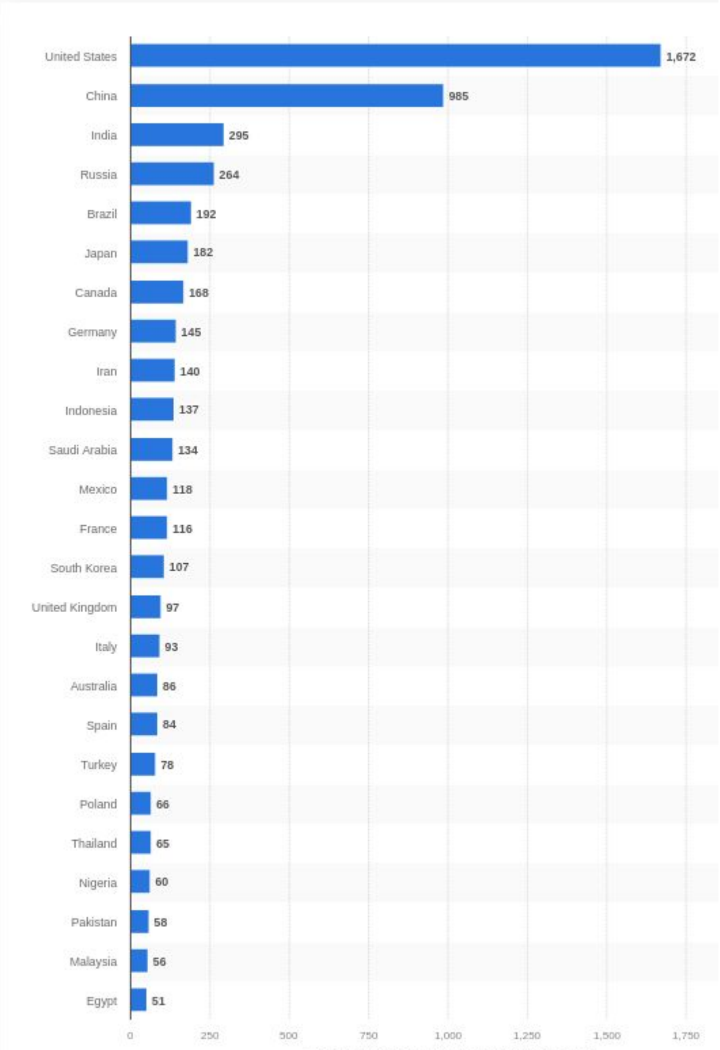
"Average annual greenhouse gas emissions growth between 2010 and 2019 slowed compared to the previous decade in energy supply (from 2.3% to 1.0%) and industry (from 3.4% to 1.4%), **but remained roughly constant at about 2% per year in the transport sector**." -IPCC

Transport emissions by country

The US is the biggest transportation emitter

Greenhouse gas emissions of the transportation sector worldwide in 2021, by select country (in million metric tons of carbon dioxide equivalent)

Worldwide; European Commission; EDGAR/JRC; Expert(s) (Crippa et al.); 2021



How are transportation emissions calculated?

How are transportation emissions calculated?

“In 1990, the Federal Clean Air Act was amended in an effort to greatly reduce air pollution. As a result, the Environmental Protection Agency devised a set of emissions standards to minimize the amount of hazardous air pollutants released by motor vehicles. This means your car may have to undergo periodic testing to ensure it’s within EPA standards and is limiting its negative impact on the environment.”

nationwide

How are transportation emissions calculated?

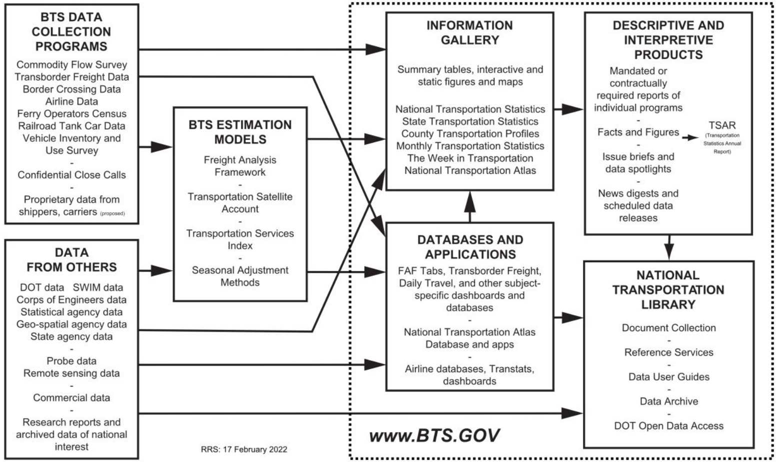
Urban cycle test:

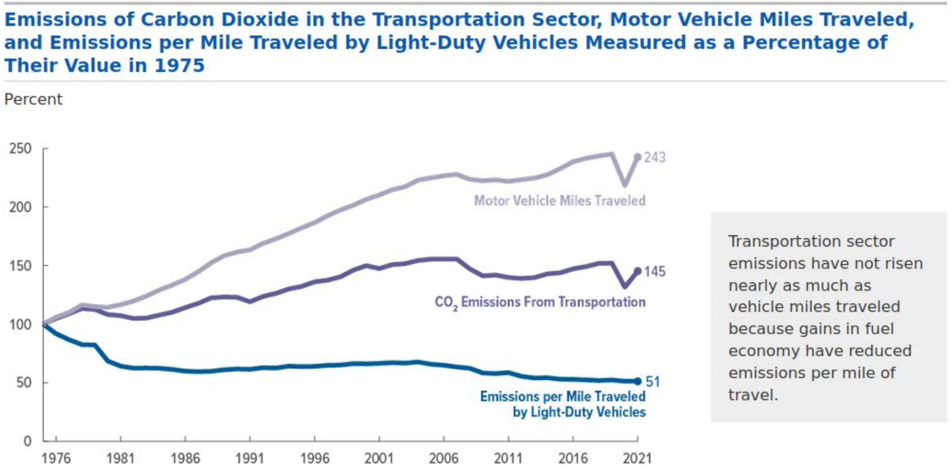
- Accelerate to 9mph in four seconds
- Cruise at 9mph for eight seconds
- Brake to rest in five seconds
- Accelerate to 20mph over 12 seconds
- Cruise at 20mph for 24 seconds
- Brake to rest in 11 seconds
- Accelerate to 31mph over 26 seconds
- Cruise at 31mph for 12 seconds
- Brake to 22mph over eight seconds
- Cruise at 22mph for 13 seconds
- Brake to rest in 12 seconds

carthrottle.com

How are transportation emissions calculated?

Bottom up method:





CBO

Getting more accurate data

The need to reduce transportation emissions

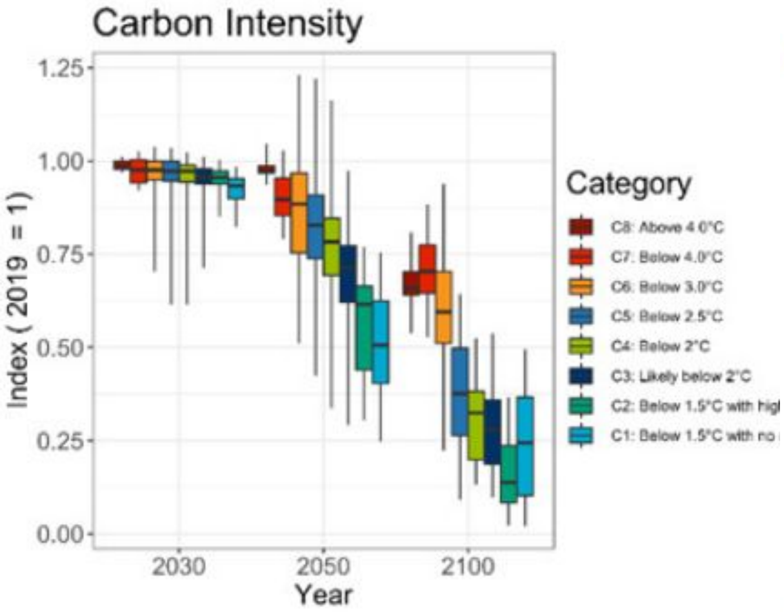
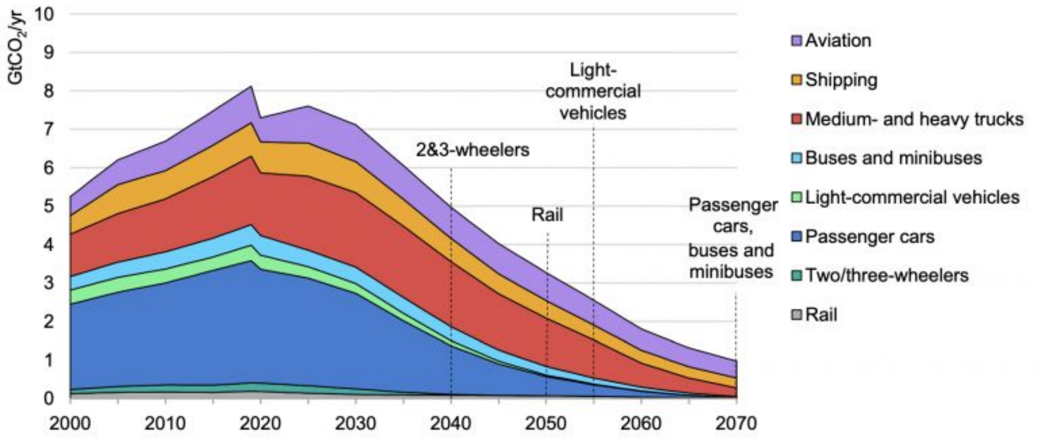


Figure 3.16 Global CO_2 emissions in transport by mode in the Sustainable Development Scenario, 2000-70



Notes: Dotted lines indicate the year in which various transport modes have largely stopped consuming fossil fuels and hence no longer contribute to direct emissions of CO_2 from fossil fuel combustion. Residual emissions in transport are compensated by negative emissions technologies, such as BECCS and DAC, in the power and other energy transformation sectors.

IPCC projections for different warming scenarios show the need for a reduction in how much carbon is emitted by transportation methods.

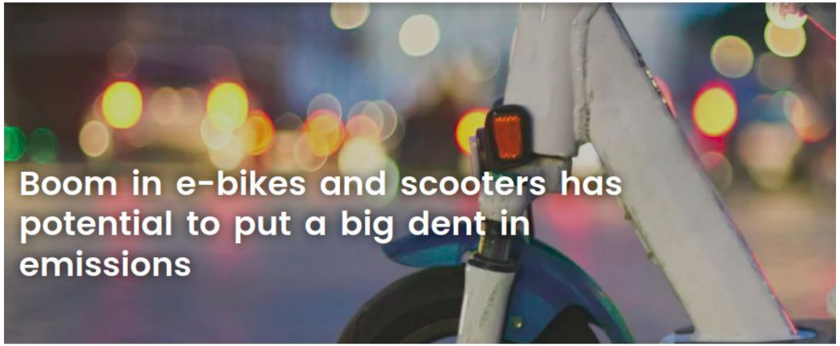
Reducing emissions from transportation

Reducing emissions from transportation

- Reduce amount of miles traveled
- Convert from high emissions forms of travel to low (aviation or single-person driving to land transport and public transportation)
- Lower emissions of fossil fuel-burning vehicles
- Switch to electric vehicles (with clean power grids)

E-bikes and scooters as alternatives to cars

The Weather Network



M.A. Jacquemain
Contributor

Published on Nov. 1, 2022, 12:43 PM

Amid rising gas prices this year, many commuters have made the switch to e-bikes and scooters, a move that has potential to drastically slash emissions in the process.

This new transportation trend has caught on in major Canadian cities, with the comparably affordable price of e-bikes and scooters seen by many customers as a way to offset historically high costs at the pumps.

Other converts have been won over by the flexibility e-bikes and scooters offer in terms of parking, storage, and navigability in traffic.

A study released earlier this year determined that the CO2 emissions produced by the energy required to run e-bikes average about 22 g/km, while gas-powered cars emit more than 250 g/km.

The research, which focused on e-bike use in England, determined that 24.4 million tons of CO2 emissions could be avoided by adopting a greater use of e-bikes, or a savings of as much as 750 kg of CO2 per person yearly.

E-bikes and scooters as alternatives to walking...

SHARED E-SCOOTERS MAY NOT BE SO CLIMATE FRIENDLY AFTER ALL

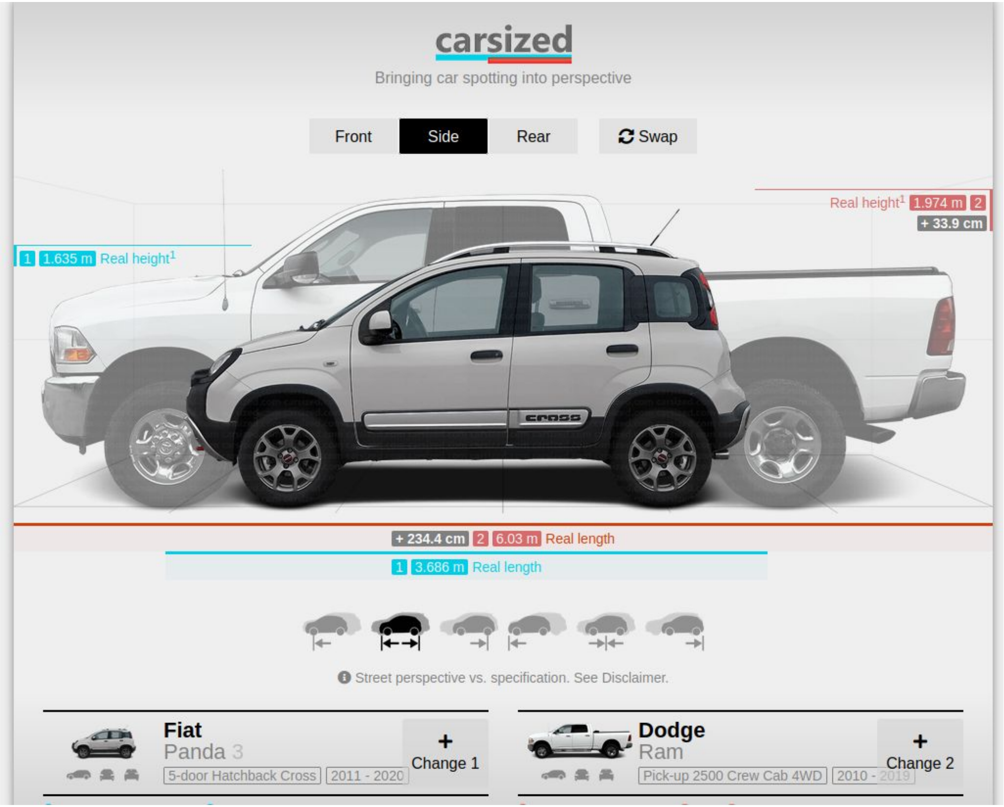
JANUARY 3RD, 2022

POSTED BY ETH ZURICH

"Shared e-scooters and e-bikes in the city of Zurich primarily replace more sustainable modes of transport—walking, public transport, and cycling. This means that they emit more carbon than the means of transport they replace," says Daniel Reck. (Credit: Getty Images)

Increasing fuel efficiency: car size

Cents Per Mile [1]			
	Size	Cost[2]	Characteristics[3]
	Subcompact	32.2	4 cylinder Avg MPG = 32
	Compact	42.3	4 cylinder Avg MPG = 23
	Intermediate	46.9	6 cylinder Avg MPG = 20
	Full-Size Vehicle	51.1	6 cylinder Avg MPG = 19
	Compact Pickup	40.2	4 cylinder Avg MPG = 18
	Full-Size Pickup	47.7	8 cylinder Avg MPG = 13
	Compact Utility	45.6	4 cylinder Avg MPG = 15
	Intermediate Utility	51.4	6 cylinder Avg MPG = 15
	Full-size Utility	52.9	8 cylinder Avg MPG = 13
	Mini-Van	50.7	6 cylinder Avg MPG = 17
	Full-Size Van	52.0	6 cylinder Avg MPG = 13



FHA

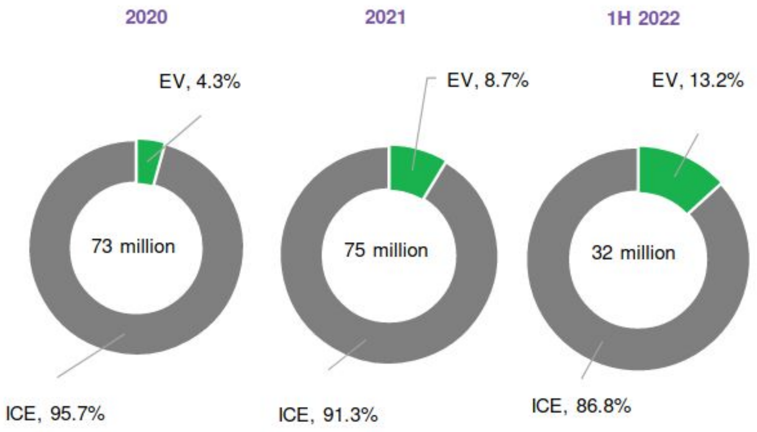
Electric vehicles

What are the reasons to want a hybrid instead of fully electric vehicle?

Electric vehicle adoption

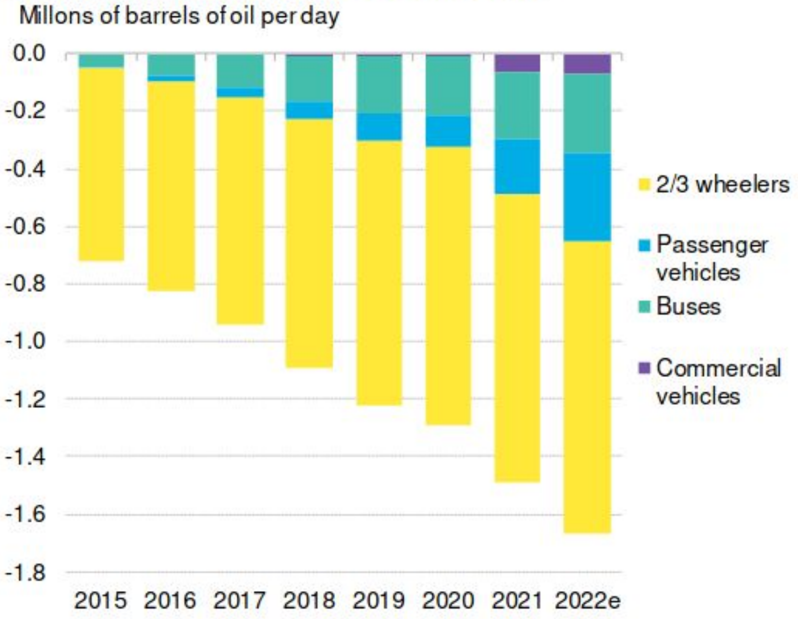
EVs are now more than 13% of the global passenger vehicle market

Global passenger vehicle sales by drivetrain



Source: BloombergNEF. Note: ICE = internal combustion engine.

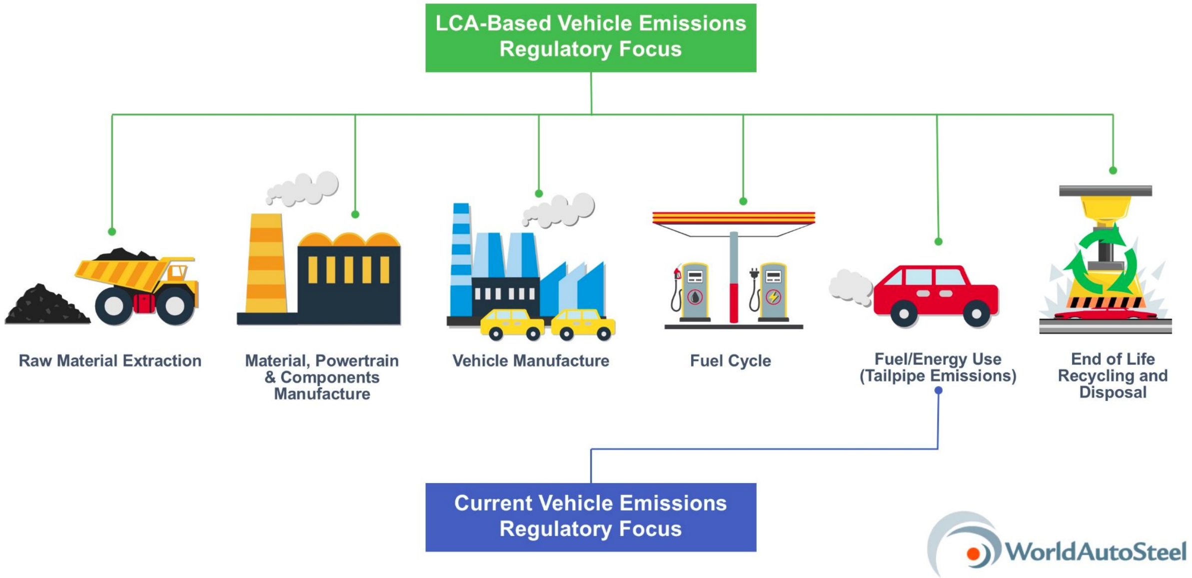
Oil demand avoided by EVs and FCVs



Source: BloombergNEF, IEA.

Life Cycle Analysis (LCA)

Life Cycle Analysis refers to the process calculating emissions for a product based on the full supply, production, and disposal chain.



Life Cycle Analysis of Electric vs Gas Cars

ELSEVIER

Renewable and Sustainable Energy Reviews
Volume 159, May 2022, 112158

Total CO_2-equivalent life-cycle emissions from commercially available passenger cars

Johannes Buberger [a], Anton Kersten [a b], Manuel Kuder [a], Richard Eckerle [a], Thomas Weyh [a], Torbjörn Thiringer [b]

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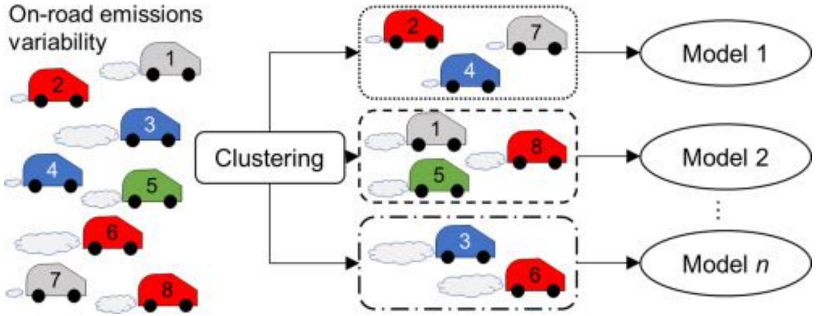
Highlights

- Quantification of the CO_2-equivalent greenhouse gas emissions of 790 different commercially available vehicle variants.
- The total life-cycle emissions of hybrid and electric vehicles are reduced by up to 89% compared to internal combustion engine vehicles.
- Modern battery recycling techniques can counterbalance the production emissions by about 60% to 65%.
- Vehicles powered by renewable fuels, such as compressed biogas, have a similar climate change impact as electric vehicles.

Opportunities for ML to measure and reduce transportation emissions

Opportunities for ML to measure and reduce transportation emissions

Increasing accuracy of emissions inventories



ELSEVIER
Science of The Total Environment
Volume 737, 1 October 2020, 139625

Modelling of instantaneous emissions from diesel vehicles with a special focus on NO_x: Insights from machine learning techniques

Clémence M.A. Le Cornec [a], Nick Molden [b], Maarten van Reeuwijk [a], Marc E.J. Stettler [a]

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Highlights

- First use of machine learning on a large dataset of on-road vehicle emissions
- Clustering groups vehicles with similar emissions behaviour
- Instantaneous emissions models developed on clusters to reduce number of models
- Artificial neural networks and non-linear regression have comparable accuracy.
- Fast instantaneous models can be used for high resolution emissions inventories.

Opportunities for ML to measure and reduce transportation emissions

Making routes more efficient, given other constraints

Operating Electric Vehicle Fleet for Ride-Hailing Services With Reinforcement Learning

Jie Shi, *Student Member, IEEE*, Yuanqi Gao, *Student Member, IEEE*, Wei Wang, *Student Member, IEEE*, Nanpeng Yu, *Senior Member, IEEE*, and Petros A. Ioannou, *Fellow, IEEE*

Abstract—Providing ride-hailing services with electric vehicles can help reduce greenhouse gas emissions and solve the last mile problem. This paper develops a reinforcement learning based algorithm to operate a community owned electric vehicle fleet, which provides ride-hailing services to local residents. The goals of operating the electric vehicle fleet are to minimize customer waiting time, electricity cost, and operational costs of the vehicles. A novel framework characterized by decentralized learning and centralized decision making is proposed to solve the electric vehicle fleet dispatch problem. The decentralized learning process allows the individual vehicles to share their operating experiences and deep neural network model for state-value function estimation, which mitigates the curse of dimensionality of state and action domains. The centralized decision making framework converts the vehicle fleet coordination problem into a linear assignment problem, which has polynomial time complexity. Numerical study results show that the proposed approach outperforms the benchmark algorithms in terms of societal cost reduction.

Opportunities for ML to measure and reduce transportation emissions

Helping Reduce Environmental Impact of Aviation with Machine Learning

Ashish Kapoor
Microsoft Corporation
1 Microsoft Way
Redmond, WA 98052
akapoor@microsoft.com

Abstract

Commercial aviation is one of the biggest contributors towards climate change. We propose to reduce environmental impact of aviation by considering solutions that would reduce the flight time. Specifically, we first consider improving winds aloft forecast so that flight planners could use better information to find routes that are efficient. Secondly, we propose an aircraft routing method that seeks to find the fastest route to the destination by considering uncertainty in the wind forecasts and then optimally trading-off between exploration and exploitation. Both these ideas were previously published in [5] and [8] and contain further technical details.

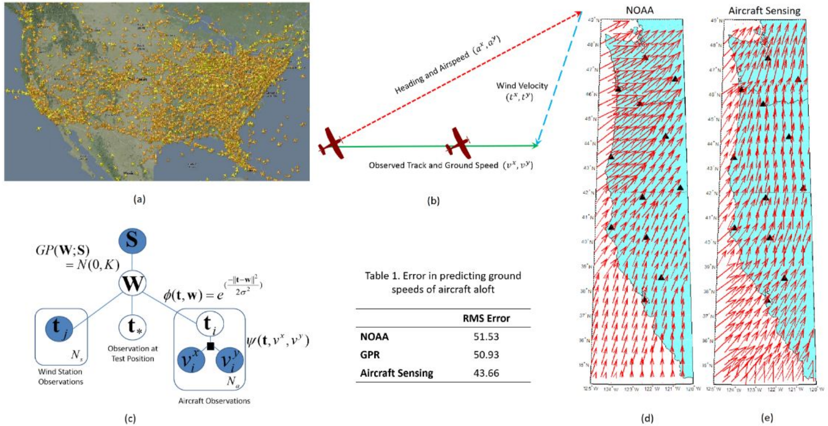
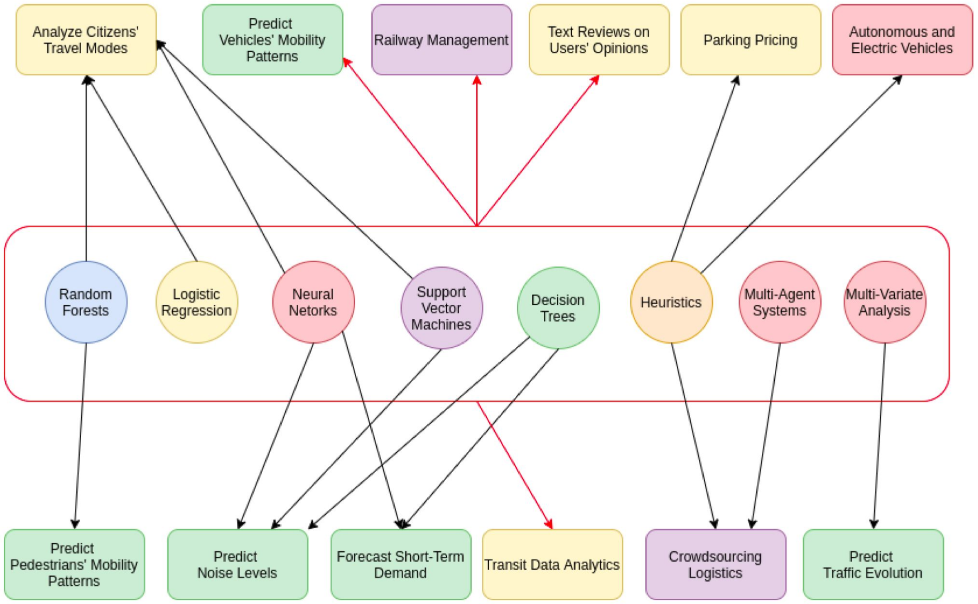


Table 1. Error in predicting ground speeds of aircraft aloft

	RMS Error
NOAA	51.53
GPR	50.93
Aircraft Sensing	43.66

Opportunities for ML to measure and reduce transportation emissions

How to optimize transport systems for cost and sustainability



Open Access Article

Simulation, Optimization, and Machine Learning in Sustainable Transportation Systems: Models and Applications

by Rocio de la Torre [1], Canan G. Corlu [2], Javier Faulin [3,*], Bhakti S. Onggo [4] and Angel A. Juan [5]

Abstract

The need for effective freight and human transportation systems has consistently increased during the last decades, mainly due to factors such as globalization, e-commerce activities, and mobility requirements. Traditionally, transportation systems have been designed with the main goal of reducing their monetary cost while offering a specified quality of service. During the last decade, however, sustainability concepts are also being considered as a critical component of transportation systems, i.e., the environmental and social impact of transportation activities have to be taken into account when managers and policy makers design and operate modern transportation systems, whether these refer to long-distance carriers or to metropolitan areas. This paper reviews the existing work on different scientific methodologies that are being used to promote Sustainable Transportation Systems (STS), including simulation, optimization, machine learning, and fuzzy sets. This paper discusses how each of these methodologies have been employed to design and efficiently operate STS. In addition, the paper also provides a classification of common challenges, best practices, future trends, and open research lines that might be useful for both researchers and practitioners.

Keywords: transportation systems; sustainability; simulation; optimization; machine learning

https://www.mdpi.com/2071-1050/13/3/1551

Opportunities for ML to measure and reduce transportation emissions

EV charging modeling

Machine Learning Approaches for EV Charging Behavior: A Review

SAKIB SHAHRIAR[1], A. R. AL-ALI[1], (Life Senior Member, IEEE),
AHMED H. OSMAN[2], (Senior Member, IEEE), SALAM DHOU[1], (Member, IEEE),
AND MAIS NIJIM[3], (Member, IEEE)
[1]Department of Computer Science and Engineering, American University of Sharjah, Sharjah, United Arab Emirates
[2]Department of Electrical Engineering, American University of Sharjah, Sharjah, United Arab Emirates
[3]Department of Electrical Engineering and Computer Science, Texas A&M University-Kingsville, Kingsville, TX 78363, USA

Corresponding author: A. R. Al-Ali (aali@aus.edu)

This work was supported in part by the Department of Computer Science and Engineering and the Open Access Program from the American University of Sharjah, United Arab Emirates.

ABSTRACT As the smart city applications are moving from conceptual models to development phase, smart transportation is one of smart cities applications and it is gaining ground nowadays. Electric Vehicles (EVs) are considered one of the major pillars of smart transportation applications. EVs are ever growing in popularity due to their potential contribution in reducing dependency on fossil fuels and greenhouse gas emissions. However, large-scale deployment of EV charging stations poses multiple challenges to the power grid and public infrastructure. To overcome the issue of prolonged charging time, the simple solution of deploying more charging stations to increase charging capacity does not work due to the strain on power grids and physical space limitations. Therefore, researchers have focused on developing smart scheduling algorithms to manage the demand for public charging using modeling and optimization. More recently, there has been a growing interest in data-driven approaches in modeling EV charging. Consequently, researchers are looking to identify consumer charging behavior pattern that can provide insights and predictive analytics capability. The purpose of this article is to provide a comprehensive review for the use of supervised and unsupervised Machine Learning as well as Deep Neural Networks for charging behavior analysis and prediction. Recommendations and future research directions are also discussed.

TABLE 1. Supervised learning for charging behavior.

Source	Charging Behavior	ML Model	Results and Impacts
[49]	Predict session duration and energy consumption from both residential and non-residential	SVR, RF and DKDE combined to form an ensembled model.	SMAPE charging duration: 10.4%, SMAPE energy consumption: 7.54%. Reduced peak load by 27%, and reduced charging cost by 4% when integrated to scheduler.
[55]	Predict session duration and energy needs for non-residential public charging space, CA, USA	Probabilistic GMM	SMAPE user duration: 12.25%, SMAPE energy consumption: 12.73%
[56]	Predict EV charging departure time	Regression including XGBoost and LR	Best result using XGB: MAE of 82 minutes for departure
[57]	Predict start time, end time, energy consumption.	LR for consumption	-
[58]	Predict arrival and departure time EVs in a university campus (non-residential)	SVMs	Average MAPE arrival time: 2.85%, departure time: 3.7%.
[60]	Predict whether the EVs will be charged the next day, and which hours they will be charged for residential dataset.	Ensembled model using RF, Naïve Bayes, AdaBoost and Gradient boosting	TPR for predicting whether the EVs will be charged: 0.996, Accuracy for predicting the hours when the EVs will be charged: 0.724
[61]	Predict energy consumption at a charging outlet in a university campus (non-residential)	KNN, Best model was with k set to 1 (1-NN)	SMAPE: 15.27%. The predictive model integrated to a mobile application can predict the end charging time and energy in 1 second
[62]	Predict the energy needs at a charging outlet in the next 24 hours for a university campus	Various ML including PSF, SVR, RF	Best result using PSF model with average SMAPE: 14.06%
[64]	Predict energy consumption of a session	PSF-based using kNN	SMAPE: 7.85%
[65]	Classify whether the driver will use fast charging	Binary log. regression	Accuracy: 0.894
[66]	Predict the time to next plug for residential charging	SVR with radial basis	MAE: 0.124 minutes, RMSE: 0.158 minutes
[67]	Predict charge profiles in workplace	XGBoost, LR and ANN	Best result using XGBoost MAE: 126 W. Addition to scheduling lead to up to 21% increase in charge.
[68]	Develop model to predict charging speed using temperature, connection time, SOC	LR	-
[69]	Predict charging capacity and daily charging times.	RF	MAPE: 9.76% 1 station. MAPE: 12.8% for groups of stations for prediction of charging load for next 15 minutes

https://ieeexplore.ieee.org/abstract/document/9194702

Opportunities for ML to measure and reduce transportation emissions

Design of EV charging infrastructure

Optimal Placement of Public Electric Vehicle Charging Stations Using Deep Reinforcement Learning

Aidan Petratos*
College of Natural Sciences, The University of Texas at Austin

Allen Ting
College of Natural Sciences, The University of Texas at Austin

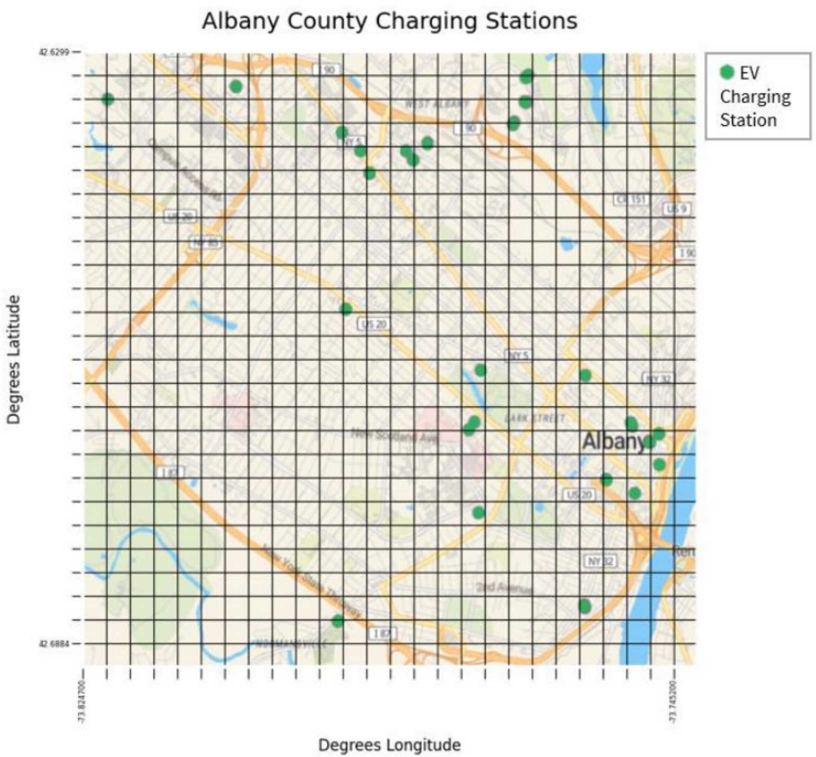
Shankar Padmanabhan
College of Natural Sciences, The University of Texas at Austin

Kristina Zhou
College of Natural Sciences, The University of Texas at Austin

Dylan Hageman
College of Natural Sciences, The University of Texas at Austin

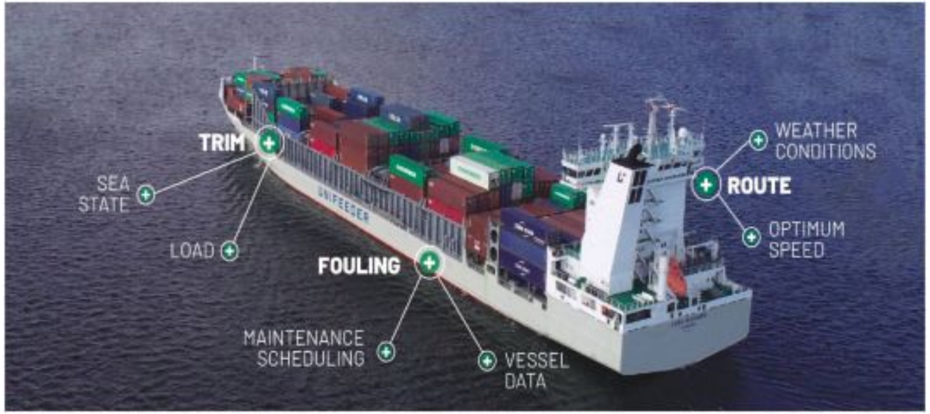
Jesse R. Pisel
Paul M. Rady School of Computer Science and Engineering, The University of Colorado at Boulder

Michael J. Pyrcz
Jackson School of Geosciences, The University of Texas at Austin



Opportunities for ML to measure and reduce transportation emissions

Optimal ship design and usage



Machine learning in sustainable ship design and operation: A review

Luofeng Huang [a], Blanca Pena [b], Yuanchang Liu [b], Enrico Anderlini [b]

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Abstract

The shipping industry faces a large challenge as it needs to significantly lower the amounts of Green House Gas emissions. Traditionally, reducing the fuel consumption for ships has been achieved during the design stage and, after building a ship, through optimisation of ship operations. In recent years, ship efficiency improvements using Machine Learning (ML) methods are quickly progressing, facilitated by available data from remote sensing, experiments and high-fidelity simulations. The data have been successfully applied to extract intricate empirical rules that can reduce emissions thereby helping achieve green shipping. This article presents an overview of applying ML techniques to enhance ships' sustainability. The work covers the ML fundamentals and applications in relevant areas: ship design, operational performance, and voyage planning. Suitable ML approaches are analysed and compared on a scenario basis, with their space for improvements also discussed. Meanwhile, a reminder is given that ML has many inherent uncertainties and hence should be used with caution.

https://www.sciencedirect.com/science/article/pii/S0029801822021904

Paper Deep Dive

Towards Indirect Top-Down Road Transport Emissions Estimation

Ryan Mukherjee Derek Rollend Gordon Christie Armin Hadzic
Sally Matson Anshu Saksena Marisa Hughes
Johns Hopkins University Applied Physics Laboratory
{firstname}.{lastname}@jhuapl.edu

Aim: predict the bottom-up calculated emissions value by using various indirect sources

Brainstorm

What kind of data would you want to have to be able to approach this problem?

What kind of methods would you apply?

How would you measure success?

If successful, how could this system be useful?

Motivation

Want to be able to apply the same estimation method globally, even where on-the-ground transportation data doesn't exist.

Multiple efforts are developing detailed bottom-up on-road emission inventories for the U.S. [17, 22]. These projects are limited from expanding globally due to the reliance on vehicle traffic and road data that is not readily available on a global scale. EDGAR sought to improve on the scope of emissions data by providing a global inventory for transportation that uses road density as a proxy to downscale emissions geographically [31]. However, some emission estimates for urban centers in EDGAR deviated from other bottom-up inventories [17] by 500%, indicating that road density is not a sufficient proxy for global high-resolution inventories.

Our work seeks to build upon these previous on-road emissions inventory methods. Our approach, illustrated in Figure 1, leverages deep learning methods for indirect estimation of on-road emissions, at a global scale, with minimal region-specific tuning effort. Our models leverage satellite imagery as their primary input, enabling them to support increased spatial resolution and temporal frequency of on-road GHG estimates.

Motivation

Measuring emissions from cars directly is hard, so try some "indirect" methods

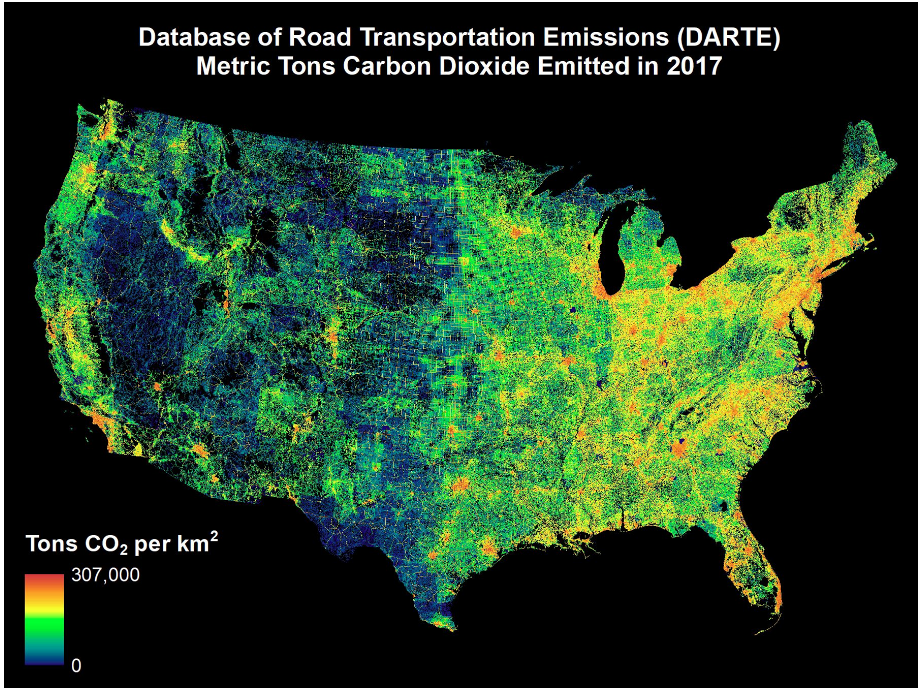
sions estimation. Vehicles are small, abundant, and frequently on the move, which makes them especially challenging to directly observe. Direct measurement of road transport emissions in a top-down manner would require substantial infrastructure and technological development to monitor and track all vehicles. For example, accomplishing this with Earth observation satellites would require new technological advancements addressing spatial resolution, night-time capability, and scalability for continuous monitoring. Currently, many relevant Earth observation systems are incapable of directly observing periods of peak vehicular activity (i.e., early morning or late afternoon commutes) because they operate in sun-synchronous orbits, such as NASA's Afternoon Constellation [42]. Additionally, many of these systems do not have sufficient spatial resolution to resolve vehicles. PlanetScope imagery [28], at 3-5 m resolution, seems to be near the limit of what can be used for monitoring vehicles [13, 7].

Data

Bottom-up inventories

3.1. Road Transport Emissions

Our models learn to regress road transportation CO_2 emissions using supervised training with the Database of Road Transportation Emissions (DARTE) [17]. DARTE provides annual (1980-2017) bottom-up CO_2 estimates at a spatial resolution of 1 km^2 covering the conterminous United States. DARTE leverages the Highway Performance Monitoring System, which provides road segments with the following properties: annual average daily traffic (AADT), functional class, urban/rural context, and county. Road seg-



Estimated based on 5 vehicle types

Data

Satellite images

3.2. Visual Imagery

Visible-spectrum satellite imagery is the primary input for our models. We use Sentinel-2 Level-2A products [14, 18] at 10 m x 10 m (100 m^2) spatial resolution. Level-2A captures bottom-of-atmosphere reflectance and incorporates radiometric calibration and orthorectification corrections from previous product stages. Sentinel-2 collects 13 spectral bands with band centers ranging from approximately 443 nm to 2190 nm. We only use bands 4, 3, and 2 from each Sentinel-2 image, which roughly correspond to visible red, green, and blue channels, respectively. These bands are stacked to form a single 3-channel RGB image, which is also referred to as a true color composite.

Data

Road maps

3.3. Roads

Road network data is used as an input to our model for three reasons: 1) it is used to generate bottom-up road transport emissions estimates, 2) their presence should be correlated with road transport emissions, and 3) it should be possible to obtain road network data globally either by using segmentation models applied to satellite data [46] or by sourcing it from governments or open-source databases like OSM [25].

To incorporate road network data, we use Rasterio [19] to create GeoTIFFs co-registered with our Sentinel-2 swaths. These GeoTIFFs use road network data extracted from shapefiles provided by the Census TIGER system [34].

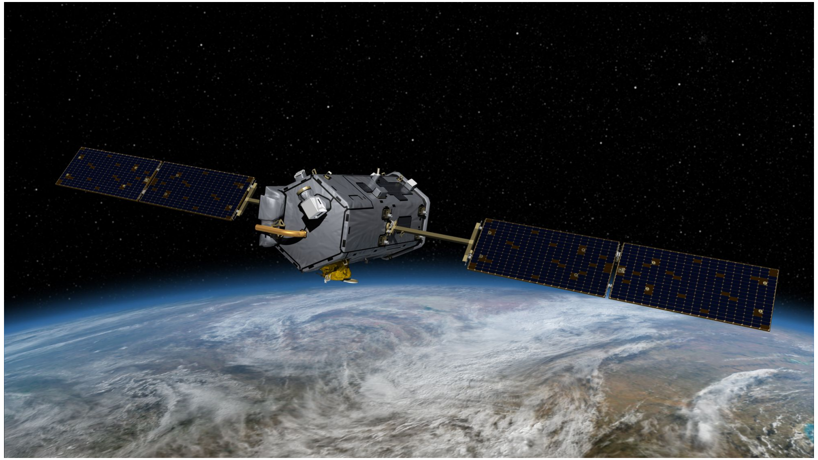
Data

CO2 estimates from remote or ground sensing

3.4. CO_2

The benefits of using additional satellite and ground-based measurements of CO_2 concentrations were also examined in this work. The Orbiting Carbon Observatory-2 (OCO-2) satellite from NASA measures column-averaged CO_2 dry air mole fraction (X_{CO_2}) in a sun-synchronous orbit with a 16 day revisit period [11]. To reduce the level

Ground-based CO_2 measurements were also explored in order to determine whether measurements taken closer to road-level offered any measurable improvement in emissions estimation accuracy. NOAA's CarbonTracker project [38] offers monthly-averaged CO_2 mole fraction estimations at 1° x 1° spatial resolution over North America, and at varying levels of the atmosphere [30]. These concentrations are derived from their optimized surface flux product that incorporates 460 observation datasets from across the globe, recorded on the ground, in aircraft, and onboard ships. Concentrations are available at 26 geopoten-



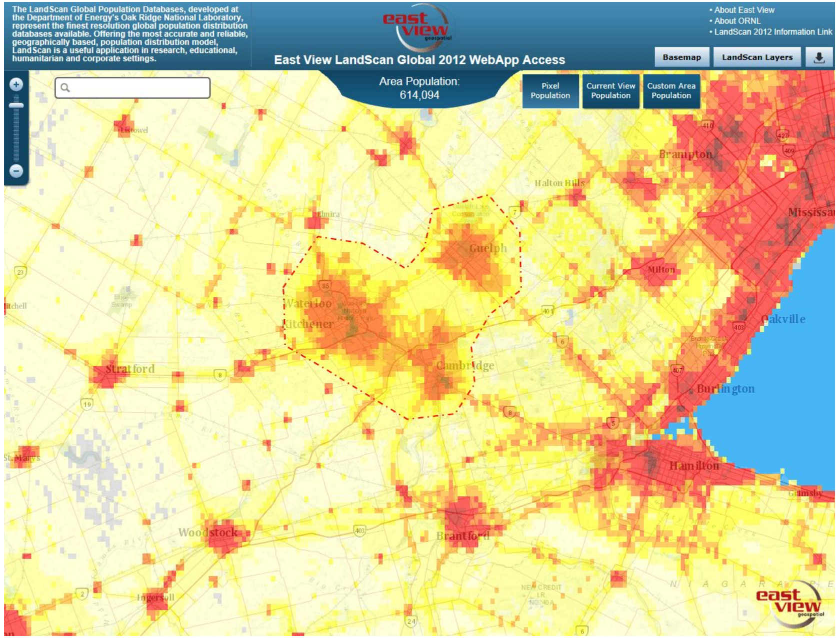
Data

Estimate population from satellite imagery

3.5. Population

Population is likely to be correlated with road transport emissions, as vehicles are still primarily operated by people and there were 1.88 vehicles per household as of 2001-2007 [2]. As such, we investigated incorporating population data into our model as an additional channel input. There

It is possible to achieve reasonable accuracy by estimating population from overhead imagery [24]. For this effort, we require annual (or sub-annual) gridded population estimates that can be paired with Sentinel-2 and DARTE data. LandScan estimates [41] provided by Oak Ridge National Laboratory meet this need. LandScan offers annual global population distribution GeoTIFFs from 2000 through 2019. For this effort, we use their 2017 product.



Data problem!

Different sources of data have different spatial and temporal resolution.

For example, satellite images here have 10m resolution, while emissions data is reported a 1km resolution. Some data sources sample every 16 days, others every month, etc.

Need to interpolate and/or average to get all data on same scale.

Data partitioned into training and test/validation sets

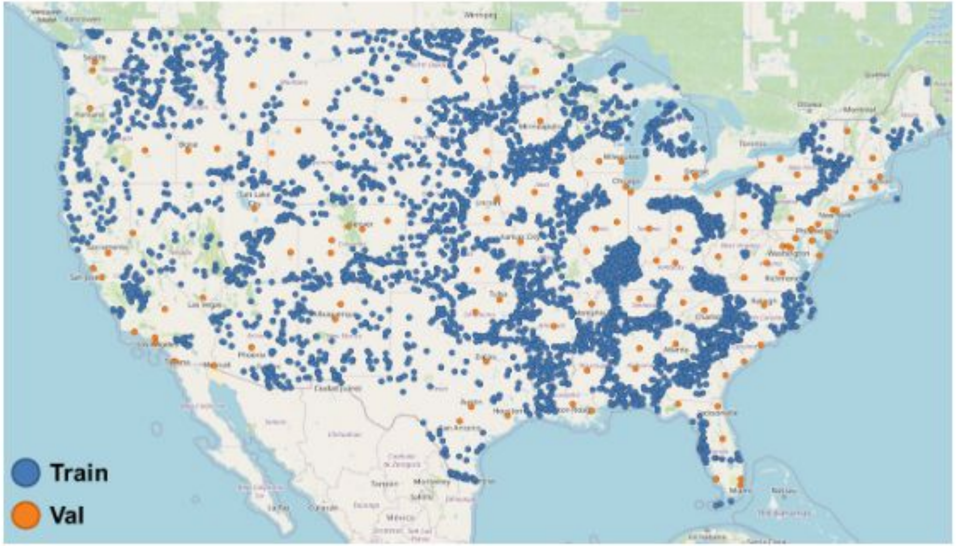


Figure 3: Plot showing city locations sampled from the conterminous United States (CONUS) for training (blue) and validation (orange).

Method

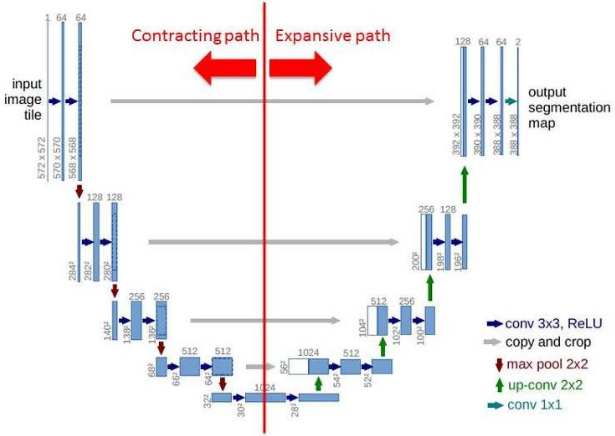
Neural Network! Want to put in image data and output an image where each pixel represents CO2 emissions from that location.

3.7. Architecture

The two base architectures we used in our experiments were U-Net [40] and MA-Net [16]. U-Nets have been a popular choice for the winning solutions of several public challenges and datasets focused on per-pixel classification and regression in both medical imaging (where they were conceived) and satellite imagery [4, 46, 21]. Both ResNet-34 [26] and EfficientNet-B3 [43] backbones were tested. Given that DARTE data has a lower resolution than Sentinel-2 imagery (1 km^2 vs 100 m^2), we also decided to modify the standard U-Net to perform reduced upsampling within the network. Given that inputs to the network had a

U-Net

Network Architecture



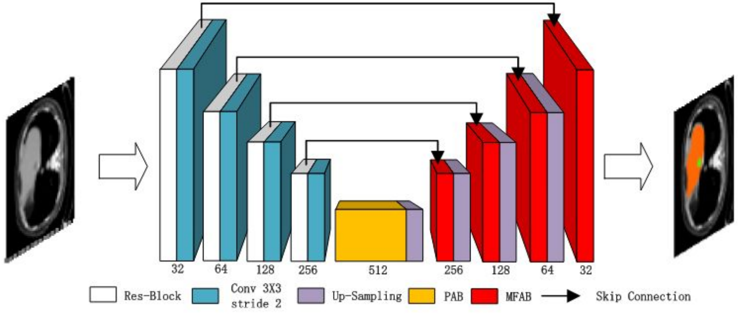
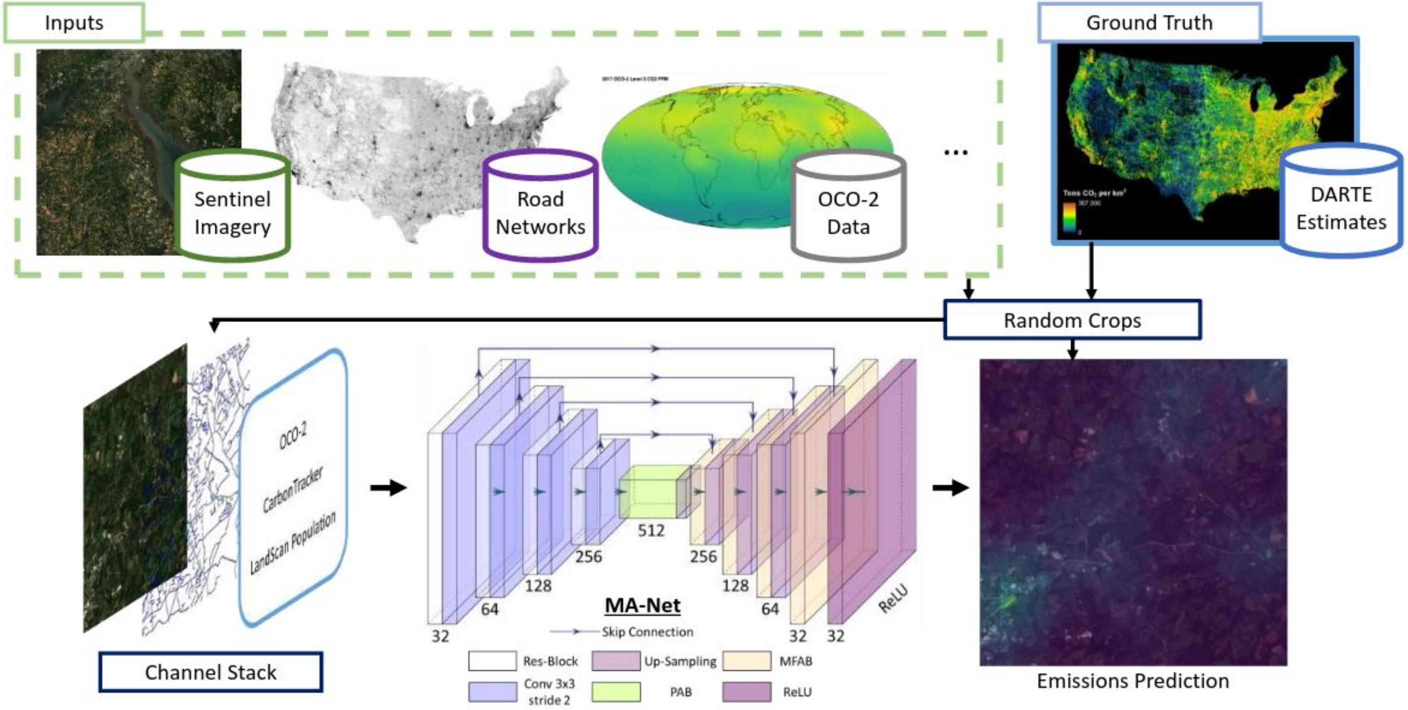


FIGURE 1. The total architecture of MA-Net.

Methods summary



Evaluation

root mean square logarithmic error (RMSLE)

RMSLE is commonly used for regression tasks where the underlying ground truth data distribution is exponential or has many outliers, expressed as follows:

$$\text{RMSLE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(log(P_i+1) - log(GT_i+1))^2}. \quad (1)$$

mean absolute percentage error (MAPE)

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\frac{|(GT_i+1) - (P_i+1)|}{GT_i+1}. \qquad (2)$$

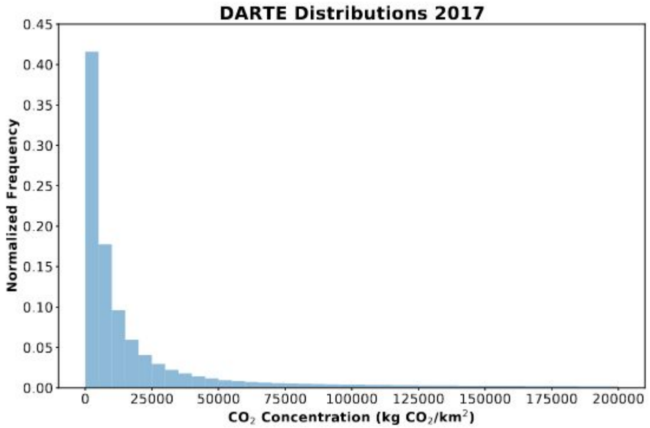


Figure 2: Histogram of DARTE road transport CO_2 emissions estimates for 2017

Tested several versions of the model trained with different combinations of data sources

Results

Results

Method	RMSLE	MAE	MAPE
RN-34 U-Net	0.661	**38.9**	50%
EN-B3 U-Net	0.710	51.2	**47%**
EN-B3 Reduced U-Net	0.836	2669.0	214%
EN-B3 MA-Net	**0.616**	39.5	55%

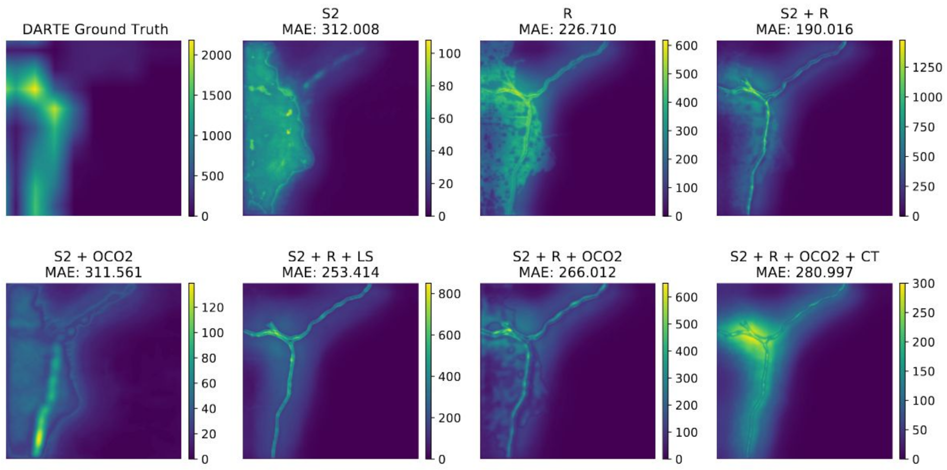
Table 1: Comparison of results across varying neural network architectures trained on Sentinel-2 and road network data, including ResNet-34 (RN-34) and EfficientNet-B3 (EN-B3) backbone U-Nets, a Reduced U-Net architecture, and an MA-Net architecture. MAE is in units of kg CO_2 per 100 m^2.

No strong winner amongst the different architectures

Results

Method	RMSLE	MAE	MAPE
S2	1.030	55.9	65%
R	0.730	43.3	64%
S2+R	**0.616**	**39.5**	55%
S2+OCO2	1.050	55.1	88%
S2+R+LS	0.739	49.9	47%
S2+R+OCO2	0.709	49.3	**46%**
S2+R+OCO2+CT	0.817	52.6	**46%**

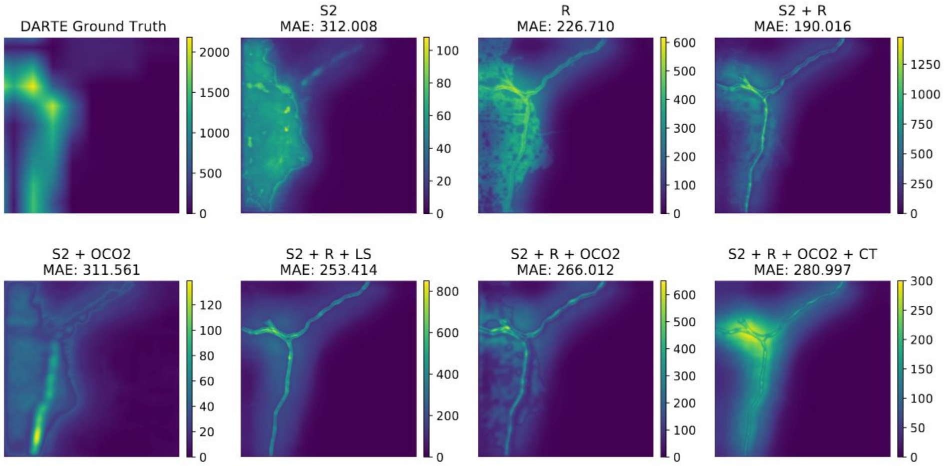
Table 2: Comparison of MA-Net results for models trained with varying inputs, including Sentinel-2 visual imagery (S2), road imagery (R), LandScan (LS) population estimates, Orbiting Carbon Observatory-2 (OCO2) Level 3 data, and CarbonTracker data (CT). MAE is in units of kg CO_2 per 100 m^2.



Satellite image and road maps alone get best absolute error. Need carbon info for lower relative error.

Results

Mismatched resolution makes evaluation hard!!



"By calculating error in a pixel-wise fashion, the model is penalized for learning fine-grained structure. In other words, if the model correctly estimates low emissions from nearby farmland, it will be penalized due to the fact that our ground truth contains large emissions values in that area."

Conclusions

Significant challenges remain to operationalize this technology. Model accuracy must be improved and estimation uncertainty quantified to provide actionable information for regional governments and municipalities. The limited availability of accurate and global road transportation emissions data must be overcome, including concerns of model transfer and regional bias. It remains to be seen if changes in government policy and human behavior over annual timescales will be captured by our models, although this hypothesis will be testable as data from 2020 emerges. Despite these challenges, we believe this work represents a critical step towards building scalable, global, near-real-time road transportation emissions inventories that can provide independent and objective feedback as the global community tackles climate change.

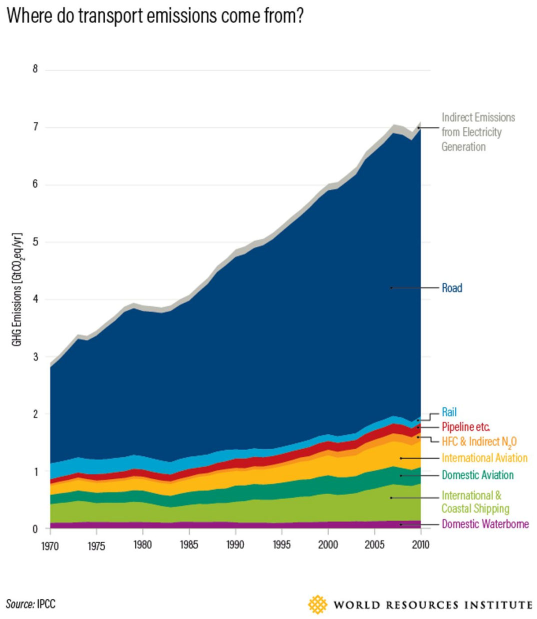
Further Resources

The geography of metropolitan carbon footprints:
https://academic.oup.com/policyandsociety/article/27/4/285/6420857

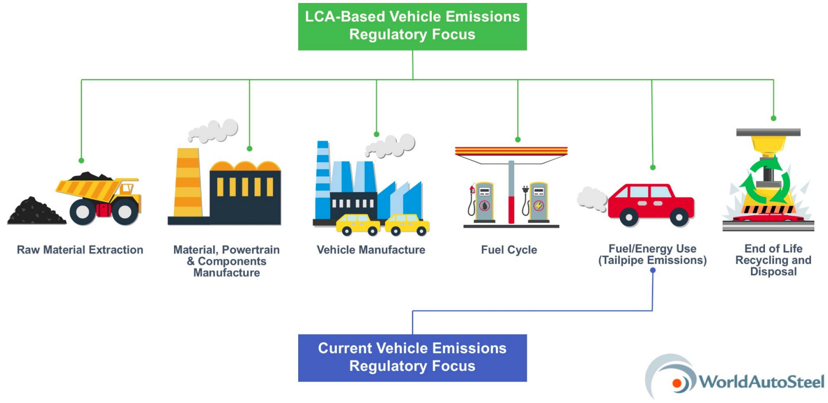
IPCC recommendations for the transport sector (section 11):
https://www.carbonbrief.org/in-depth-qa-the-ipccs-sixth-assessment-on-how-to-tackle-climate-change/

Electric vehicle factbook:
https://assets.bbhub.io/professional/sites/24/2022-COP27-ZEV-Transition_Factbook.pdf

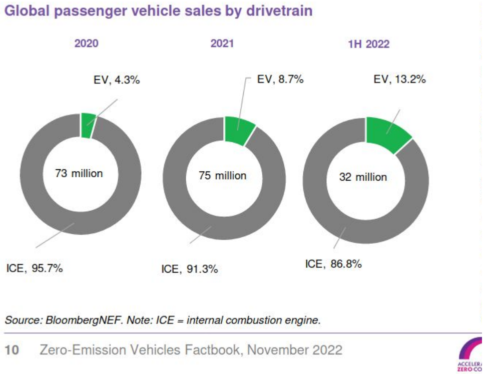
Summary



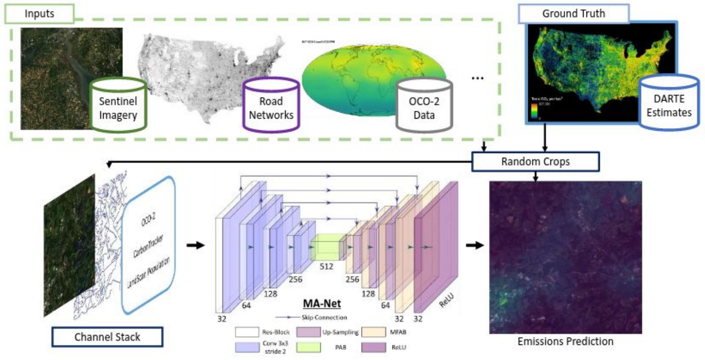
Where do transport emissions come from?
GHG Emissions [GtCO2eq/yr]
8
7
6
5
4
3
2
1
0
1970
1975
1980
1985
1990
1995
2000
2005
2010
Indirect Emissions from Electricity Generation
Road
Rail
Pipeline etc.
HFC & Indirect N2O
International Aviation
Domestic Aviation
International & Coastal Shipping
Domestic Waterborne
Source: IPCC
WORLD RESOURCES INSTITUTE



LCA-Based Vehicle Emissions Regulatory Focus
Raw Material Extraction
Material, Powertrain & Components Manufacture
Vehicle Manufacture
Fuel Cycle
Fuel/Energy Use (Tailpipe Emissions)
End of Life Recycling and Disposal
Current Vehicle Emissions Regulatory Focus
WorldAutoSteel



Global passenger vehicle sales by drivetrain
2020
2021
1H 2022
EV, 4.3%
EV, 8.7%
EV, 13.2%
73 million
75 million
32 million
ICE, 95.7%
ICE, 91.3%
ICE, 86.8%
Source: BloombergNEF. Note: ICE = internal combustion engine.
10 Zero-Emission Vehicles Factbook, November 2022



Inputs
Sentinel Imagery
Road Networks
OCO-2 Data
Ground Truth
DARTE Estimates
Random Crops
Channel Stack
MA-Net
Emissions Prediction