MethaNet - an AI-driven approach to quantifying methane point-source emission from high-resolution 2-D plume imagery

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ICML Conference

Caltech

RESNICKINSTITUTE
science + energy + sustainability

Jet Propulsion Laboratory
California Institute of Technology

Our climate is changing

greenschoolsns.ca

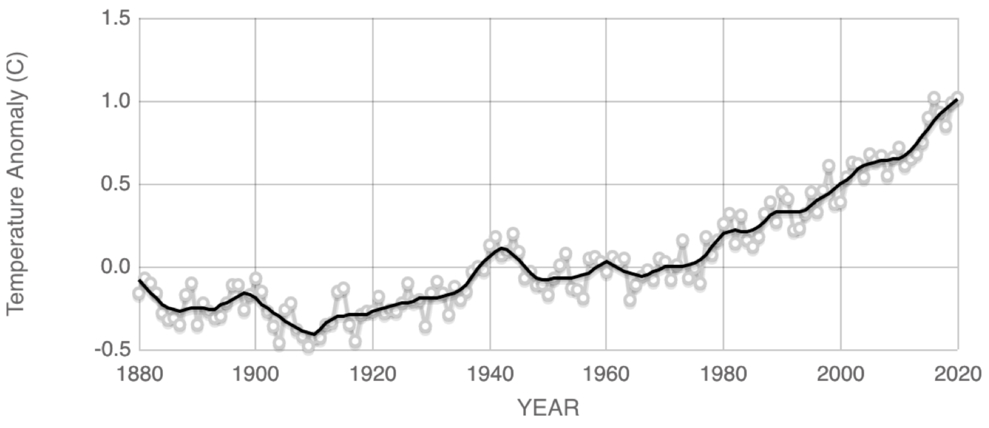
canadiangeographic.ca

nj.alumni.columbia.edu

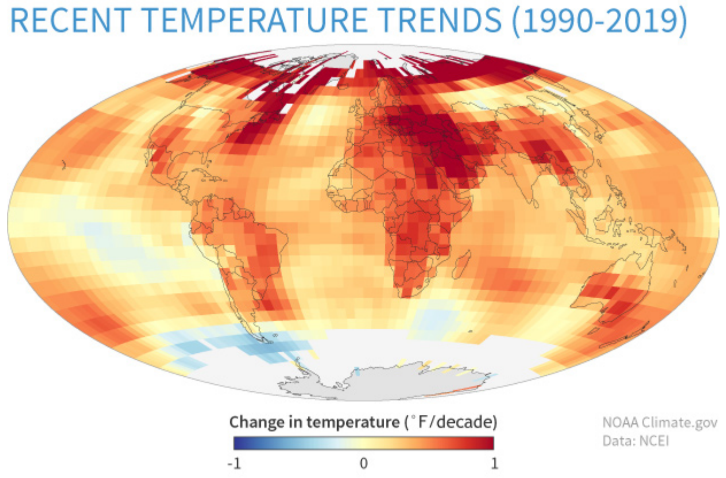
$1.16 trillion in damages

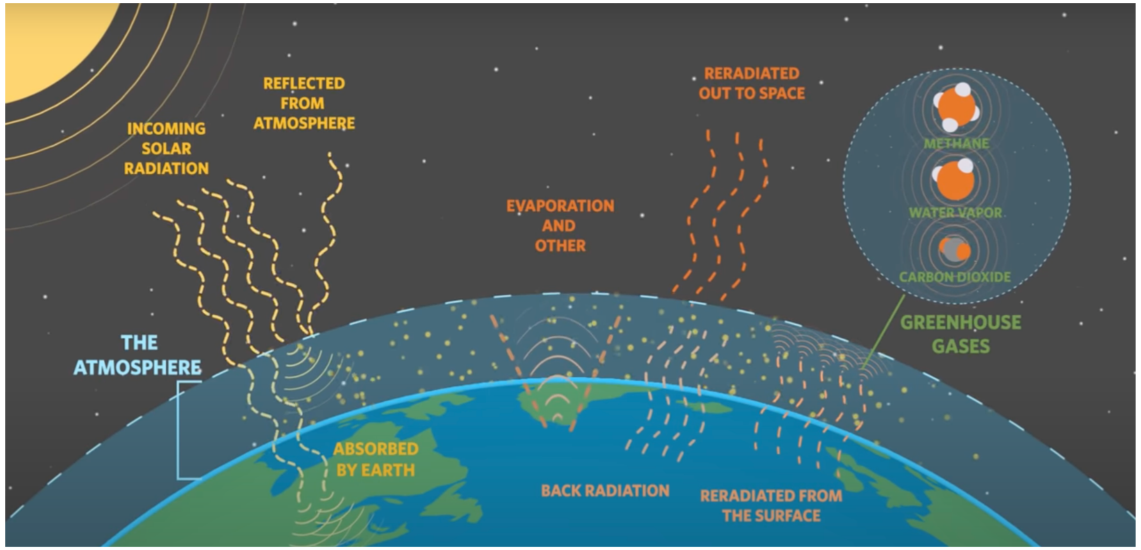
Over the past 15 years (2005-2019), weather and climate disasters have cost a combined $1.16 trillion in damages in the U.S. alone (NOAA).

Rising surface temperature



Source: climate.nasa.gov

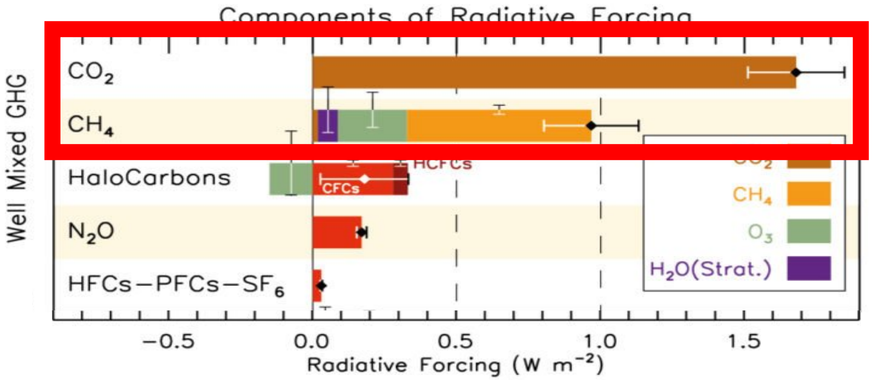




source: california academy of sciences

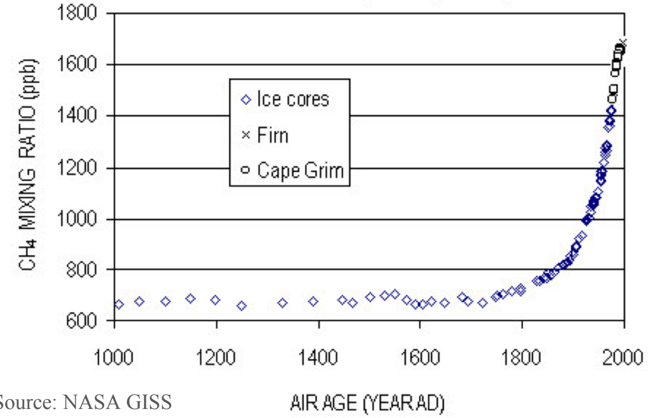
Greenhouse gases in the atmosphere lead to additional radiative forcing.

CH_4 is a key anthropogenic greenhouse gas

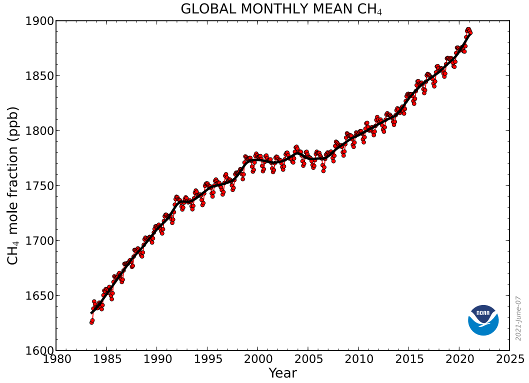


Contribution from each anthropogenic gas since 1850 (IPCC, 2013)

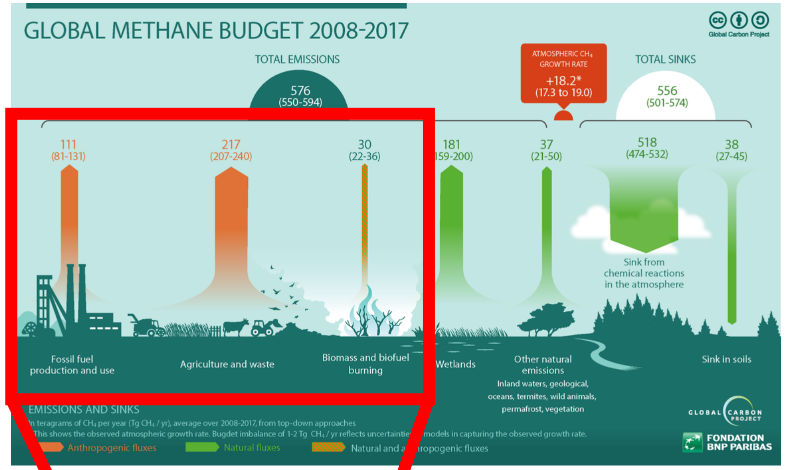
- Lifetime of CH_4 (~ 9 years) is shorter than CO_2 (~500 years) by two orders of magnitude.
- Reduction of CH_4 emissions can
  - lead to short- and medium-term mitigation.
  - help achieve Paris agreement of 1.5-2.0 °C by 2050.



Source: NASA GISS



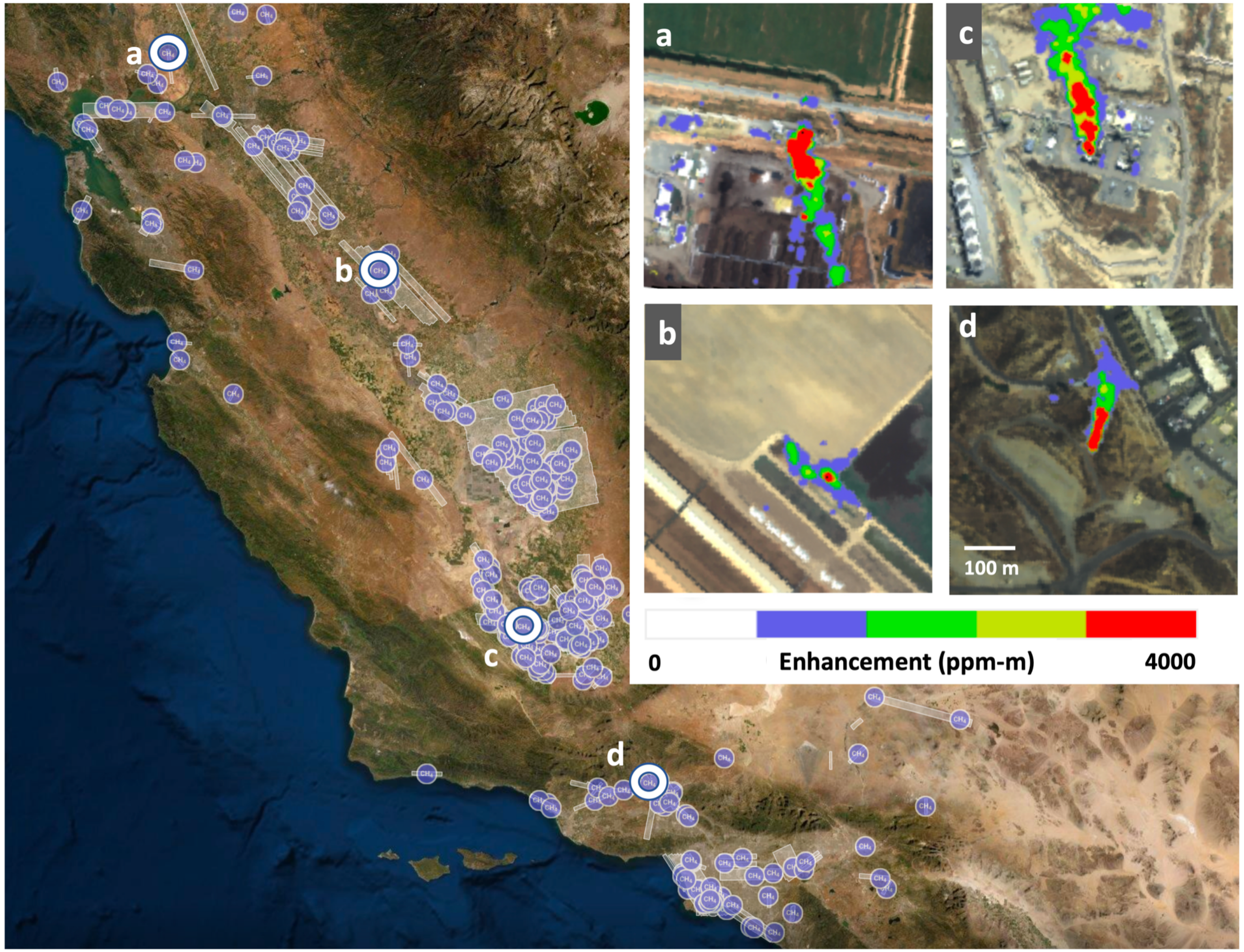
Source: NOAA



Saunois et al. 2020

60% of total emission is anthropogenic
where we can make most progress on mitigating
But local sources are uncertain/not known everywhere

Airborne remote-sensing measurements



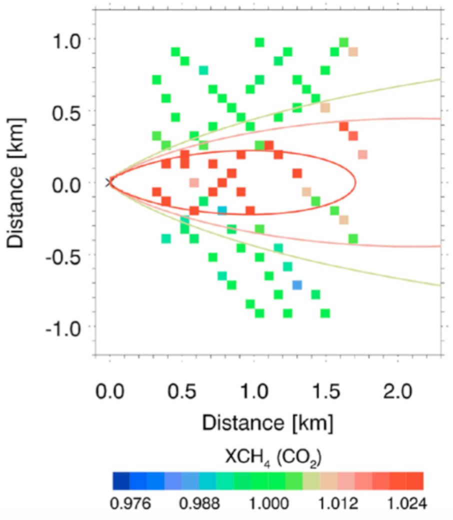
Examples of methane plumes from different sectors such as (a) a landfill, (b) diary manure area, (c) an oil and gas facility, and (d) a natural gas storage field in California, observed by the next-generation Airborne Visible/Infrared Imaging Spectrometer (AVIRIS-NG). (California Methane Source Finder)

- Airborne remote-sensing instruments such as AVIRIS-NG allow local point sources to be detected across large geographical areas.
- Each plume image represents the total CH4 column enhancement; in each pixel, the enhancement is obtained as a retrieval product using absorption spectroscopy.
- Anthropogenic emissions are often point sources.

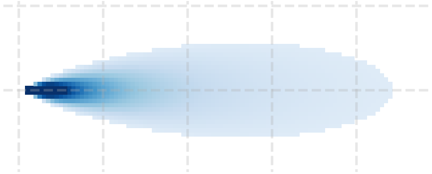
Quantification of emission rates is challenging

Previous methods rely on wind measurements

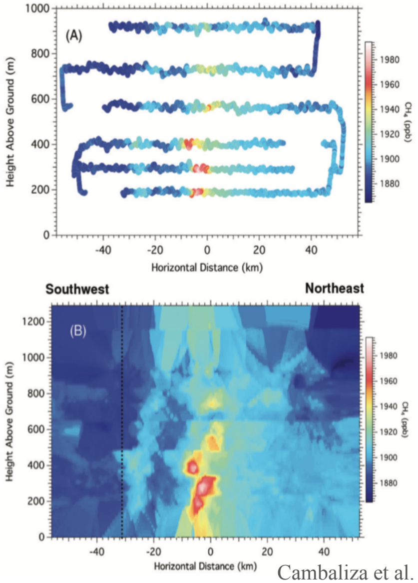
Gaussian plume modelling



Krings et al. 2013

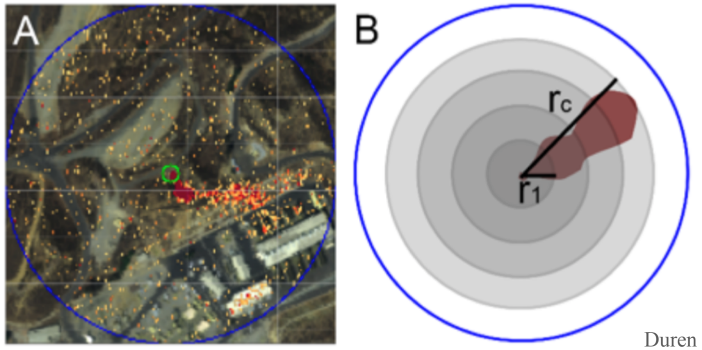


Cross-sectional flux

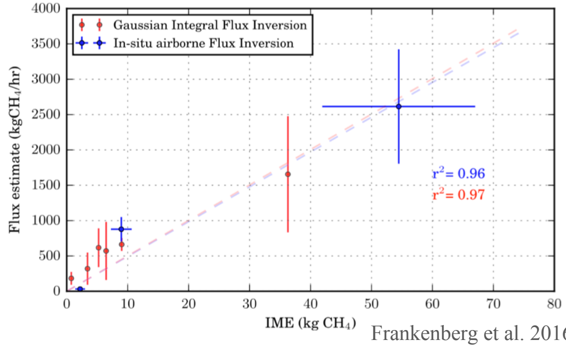


Cambaliza et al. 2015

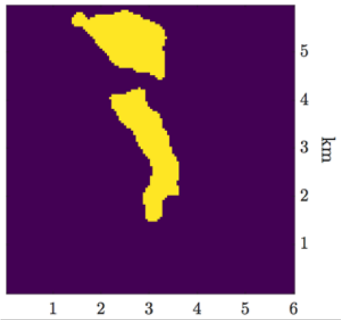
Residence time of methane mass (IME)



Duren et al. 2019



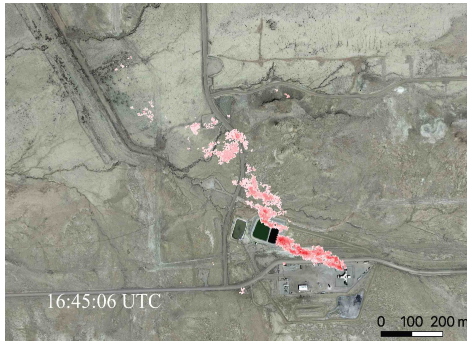
Frankenberg et al. 2016



Varon et al. 2018

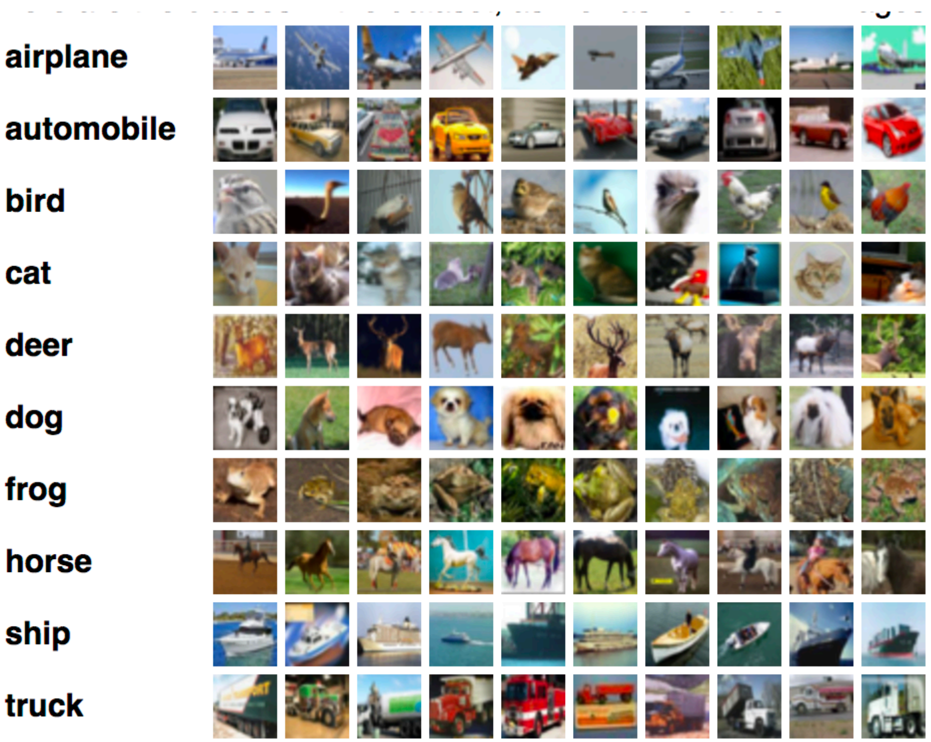
These methods need local wind knowledge.
High uncertainties from wind speeds!

What we want is to predict emission rate directly from a 2D image:

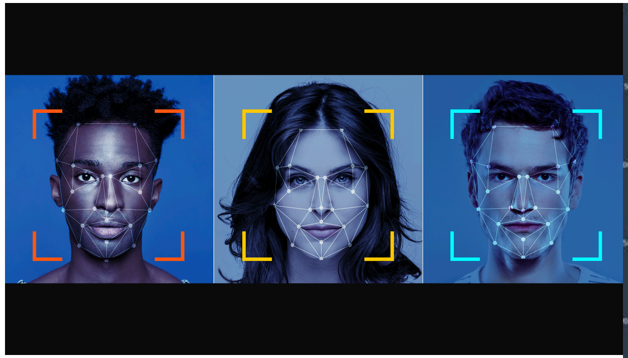


→ Emission rate

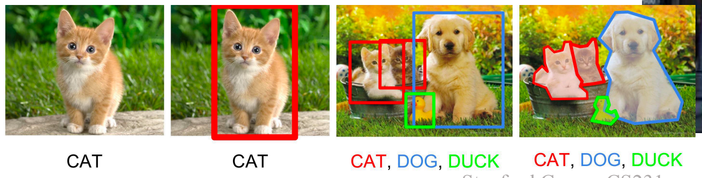
Deep learning has found tremendous success in vision tasks



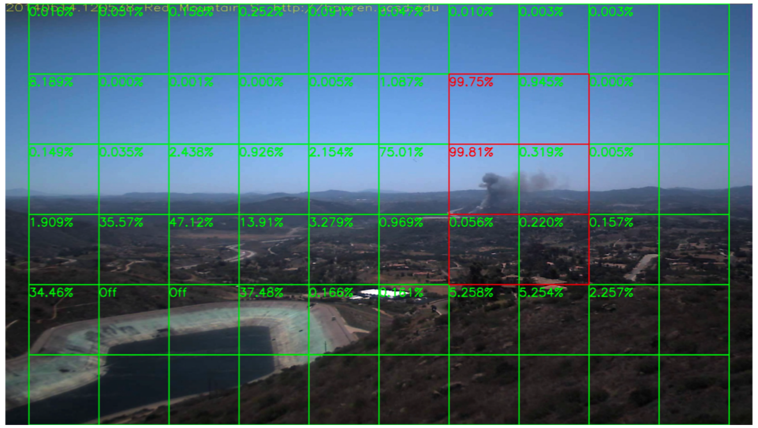
CIFAR-10

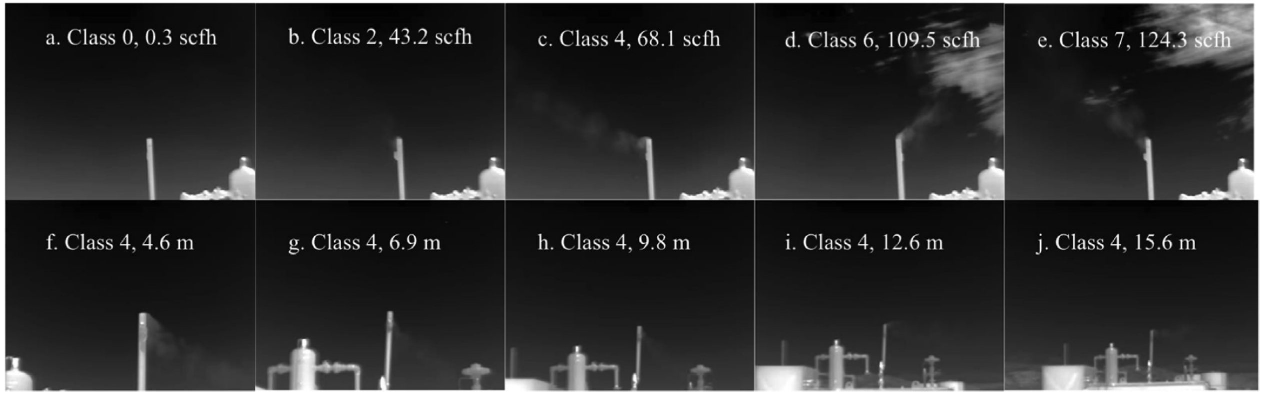

Microsoft

Ilija,Towards Data Science



Stanford Course CS231n

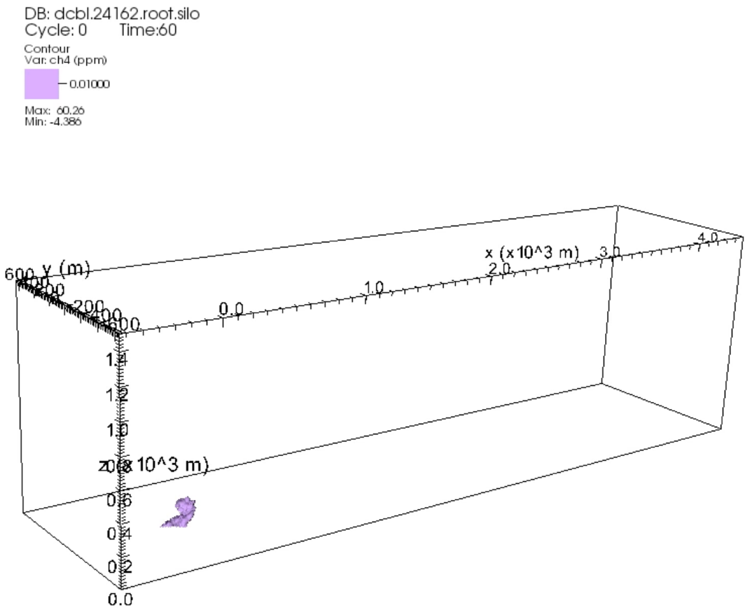

Pan et al. 2020

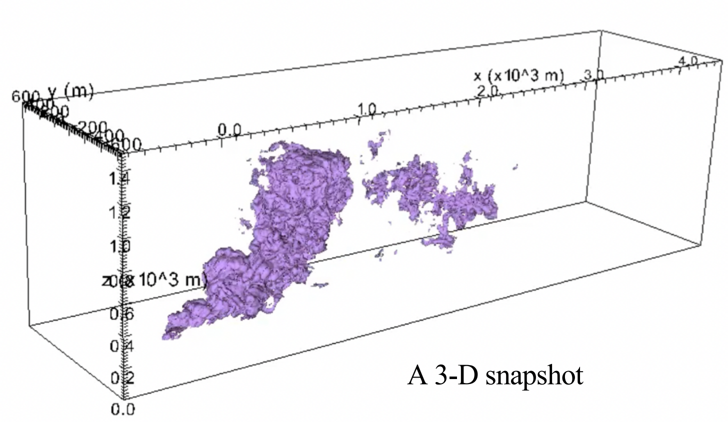


Wang et al. 2020

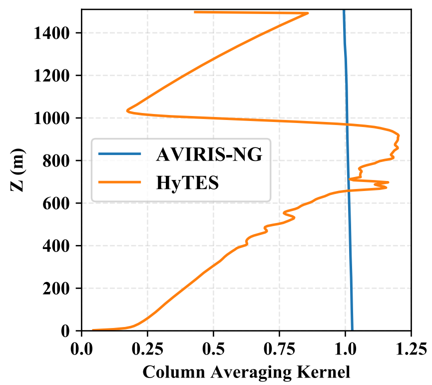
Large Eddies Simulation (LES) generates realistic plumes

LES video





A 3-D snapshot



(Instrument vertical sensitivity)

LES runs

- 3-D snapshots
- background geostrophic wind speeds of 1-10 m s^{-1}
- Emission rates in 0-2000 kg h^{-1}

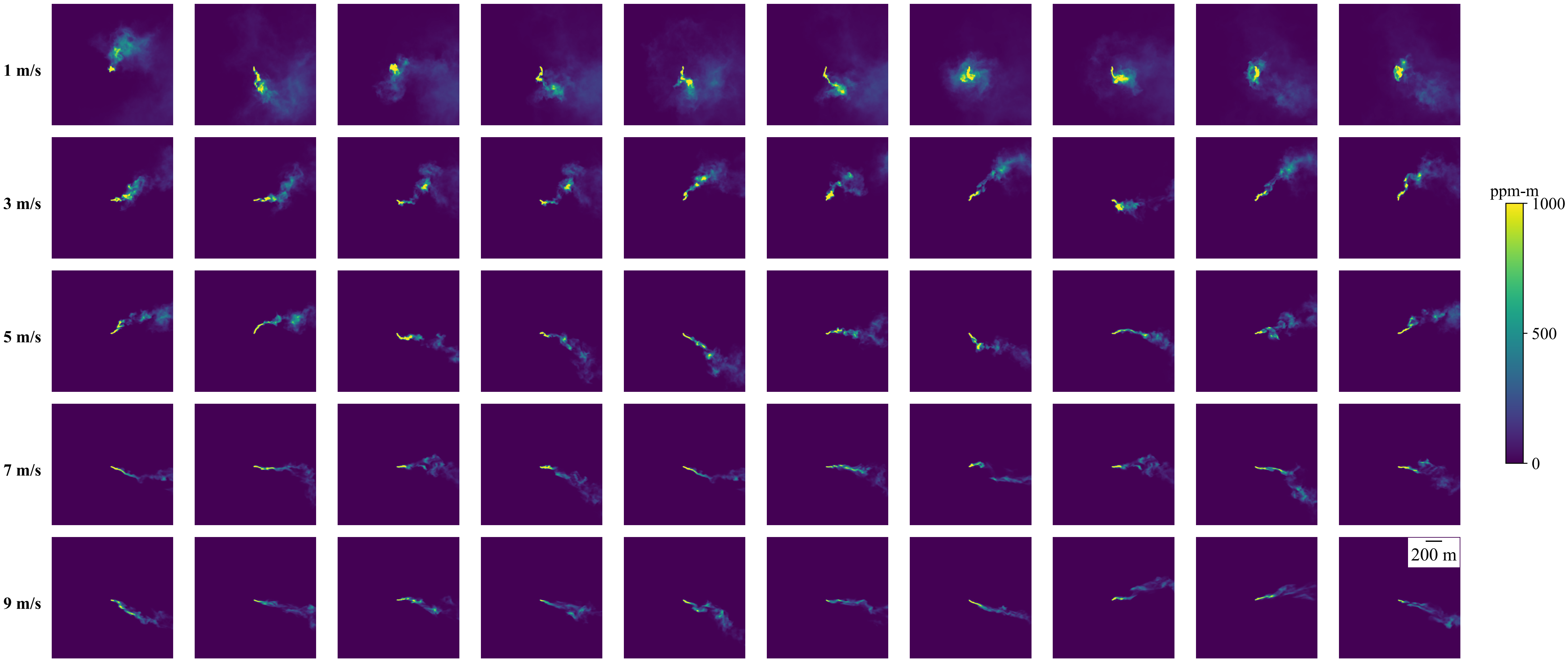
Integrate vertically

w/ AVIRIS-NG instrument sensitivity

Ensemble of synthetic 2-D plume images

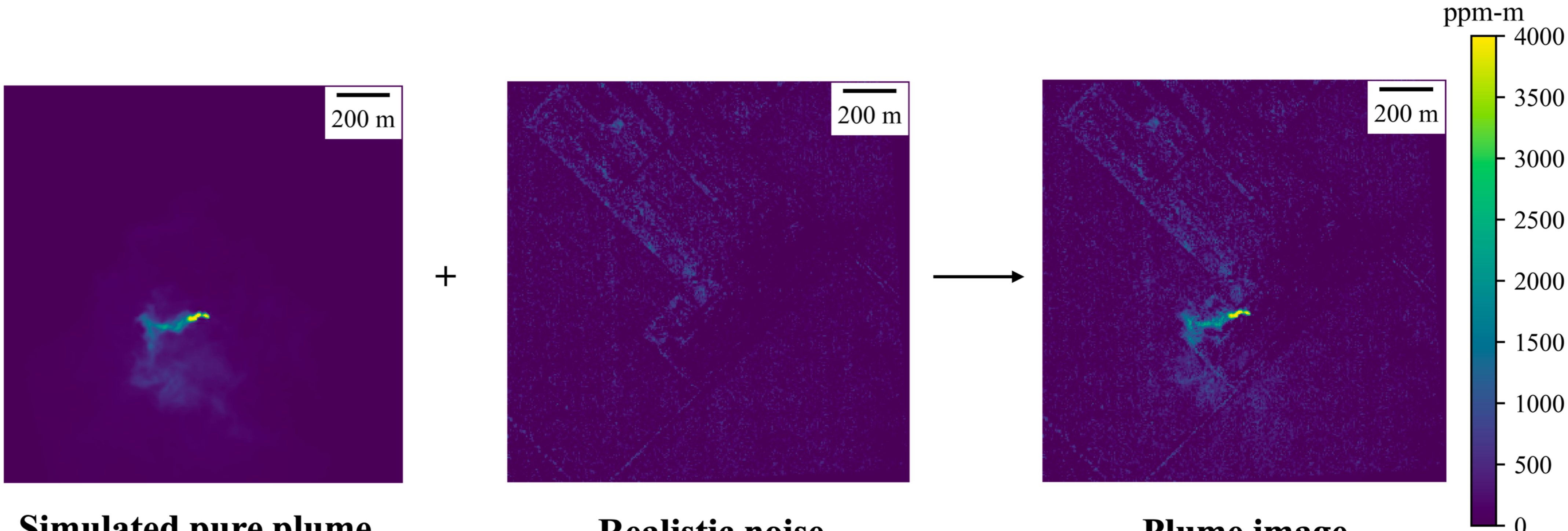
We use this to learn how plume images change with wind speeds and flux rates.

LES can simulate a variety of plumes



We apply deep learning to predict emission rates from plume images (a regression task).

Synthetic plume images with realistic noise



Simulated pure plume

Realistic noise

(From AVIRIS-NG scenes with no plumes)

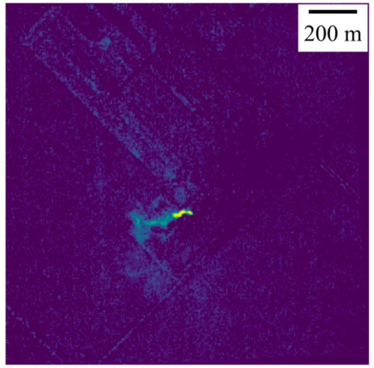
Plume image

> 250,000 synthetic images

(various emission rates, orientations, added noise from urban, desert and agriculture areas)

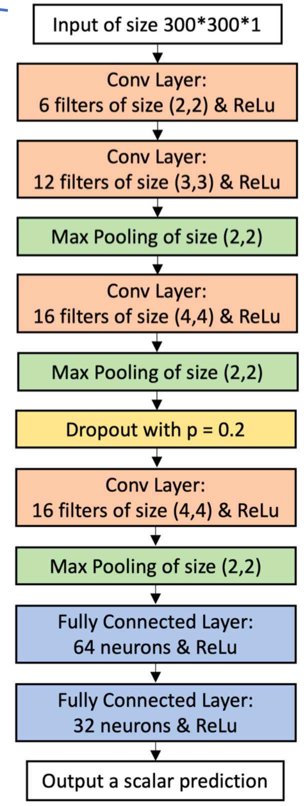
Training a customized CNN model - MethaNet

X (300*300 pixels image)



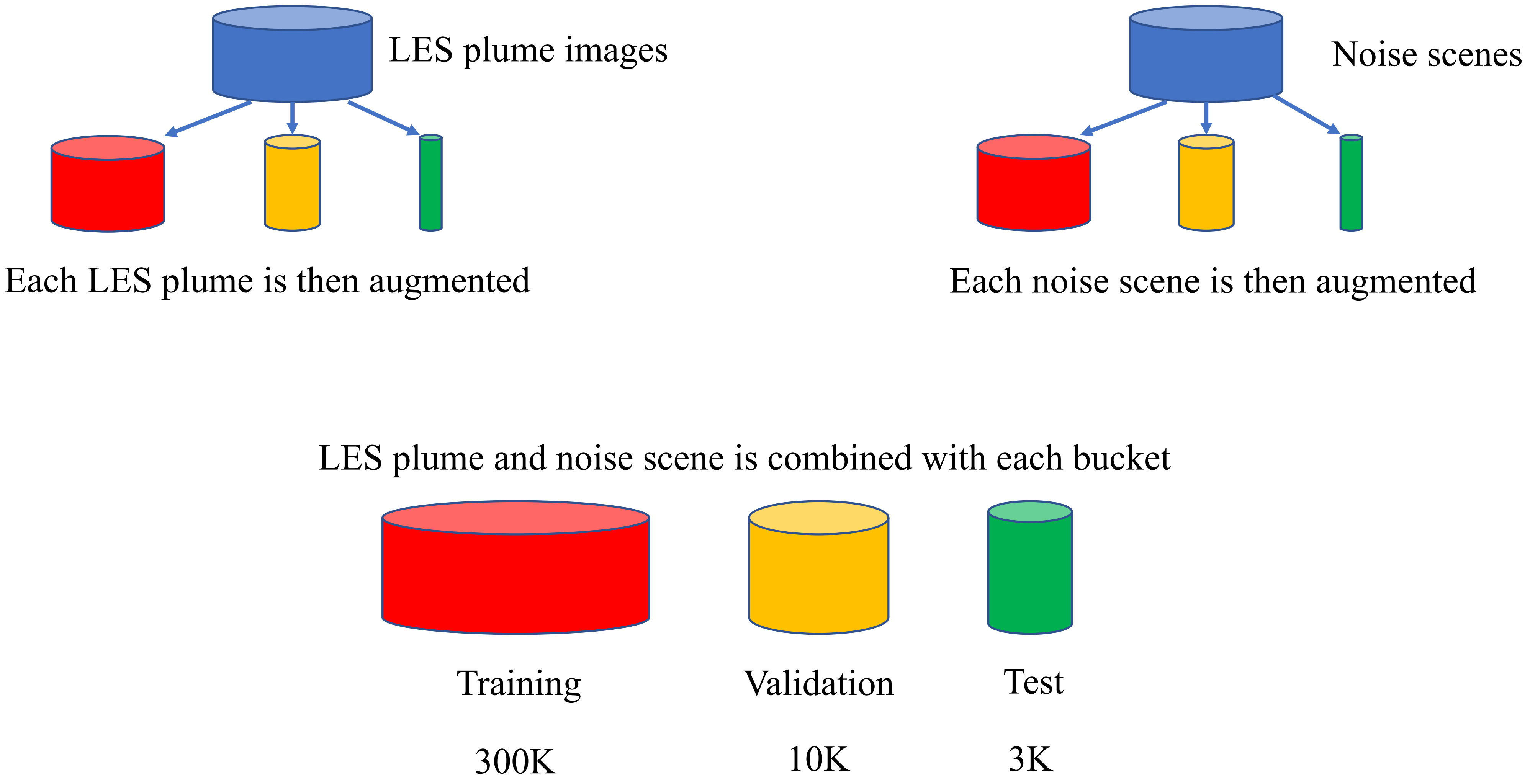
Y (scalar value)

Emission rate: 200 kg h^{-1}

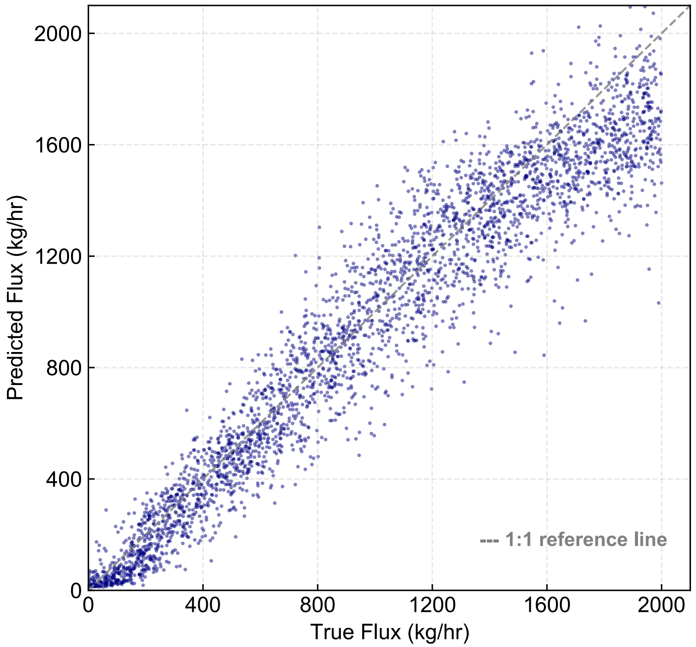


- The model learns on the training set to tune the weights of the network architecture.
- The trained model can be applied to predict unseen plumes and evaluate how well it performs.

Data preparation to ensure no contamination

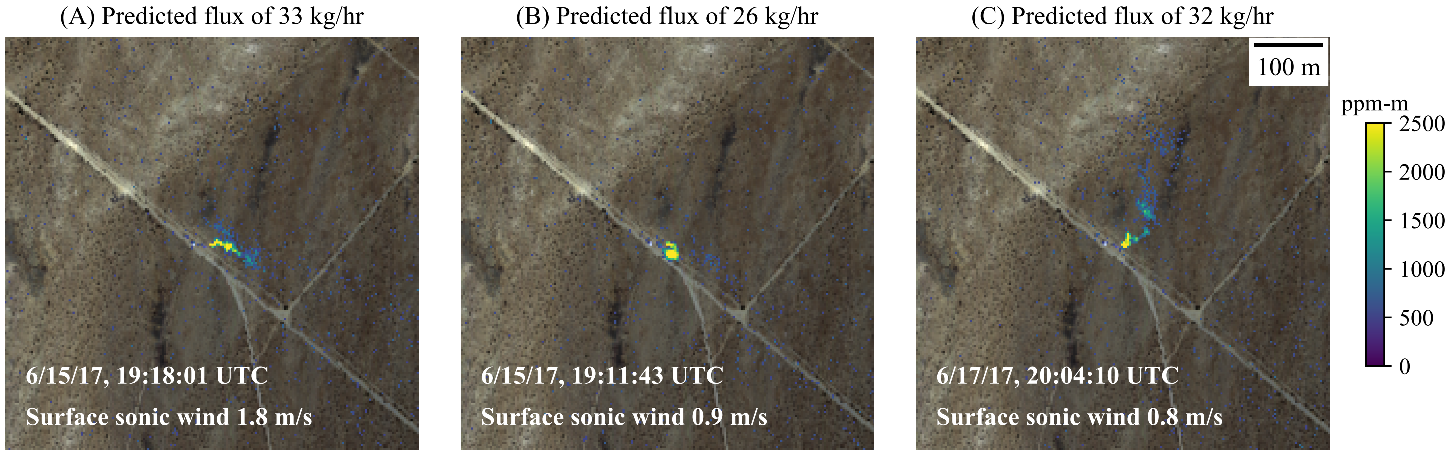


MethaNet can predict emission rates from 2D images



MethaNet performance on test set

Predictions on controlled release experiments in Victorville, CA
Controlled emission rates of 39 ± 5 kg h^{-1}



Overall:

Mean absolute percentage error of 22%.

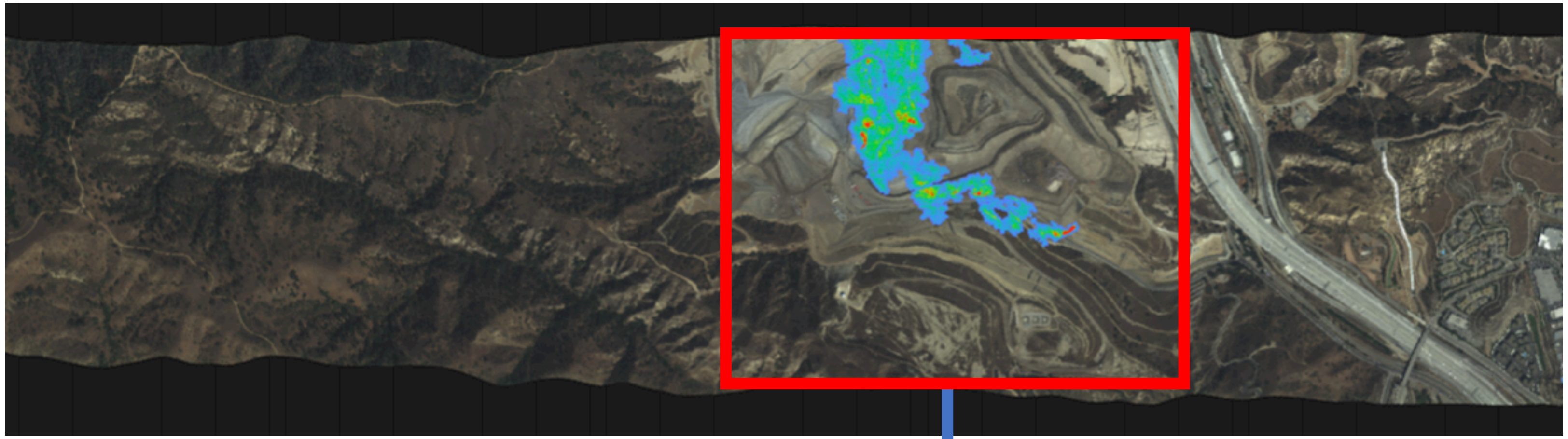
Plumes with emission rates > 40 kg h^{-1}:

Mean absolute percentage error of 17%.

- This level of performance at a mean absolute percentage error of 17% is a state-of-the-art achievement for a model that does not even rely on wind speed information.

Predicted 33, 26, and 32 kg/hr. The mean and std are 31 and 3, respectively. This is consistent with the actual rate within one std.

Conclusions



MethaNet

Emission rate

- We trained a CNN model, called MethaNet, to predict methane point-source emissions directly from high resolution 2-D plume images.
- Our model achieved a mean absolute percentage error for predicting unseen plumes under 17%, a significant improvement from previous methods that require local wind information.
- Application of MethaNet to a controlled release experiment provides a basis of this technique to be used in future airborne campaigns and satellite observations to quantify methane sources.

THANK YOU!