Surrogate Modeling for Methane Dispersion Simulations Using Fourier Neural Operator

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Tackling Climate Change with Machine Learning: workshop at NeurIPS 2022

Motivation: Methane Leak Detection & Remediation (LDAR)

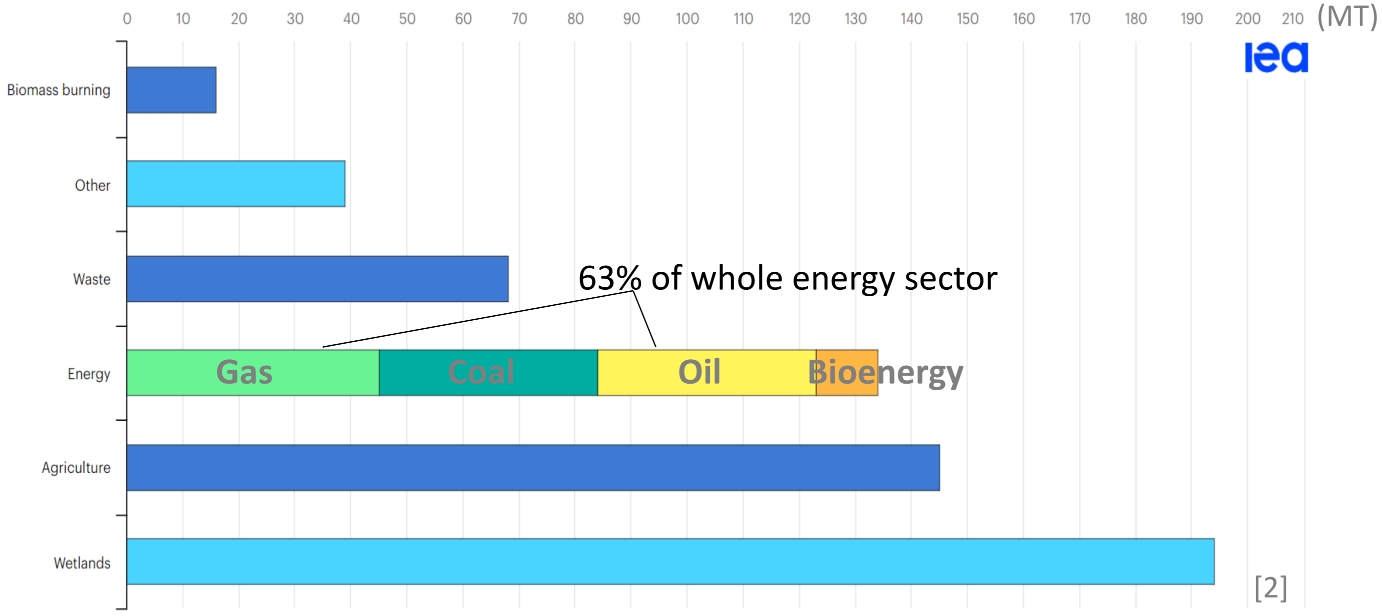
2nd
Most potent Greenhouse Gas (GHG)

x 84-87
20-year Global Warming Potential (GWP) than CO_2 [1]

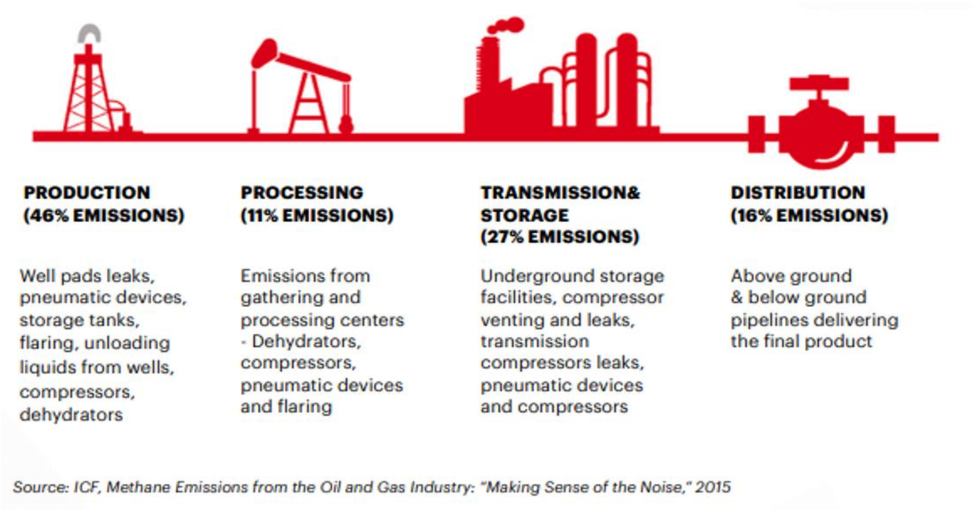
75%
Methane emissions from O&G can be avoided [1]

40%
Avoided with no net cost [1]

Sources of Methane Emissions



Methane Leakage across the O&G Value Chain



[1] IPCC Fourth Assessment Report
[2] IEA, Sources of methane emissions, IEA, Paris https://www.iea.org/data-and-statistics/charts/sources-of-methane-emissions-2

Methane source attribution workflow

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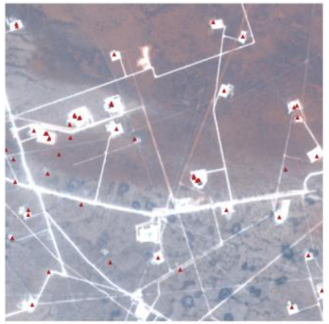
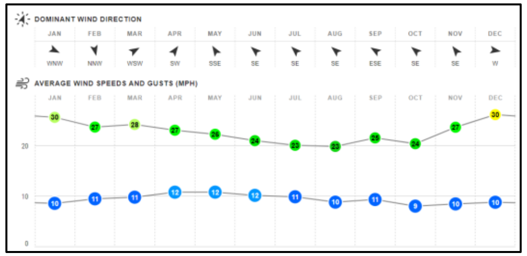
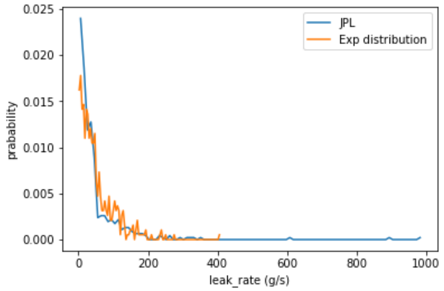




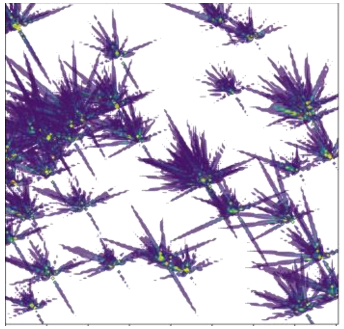


Oil & Gas facility map (well pads, pipelines, processing plants …)

Meteorology variables (wind speed, direction, solar radiation …)

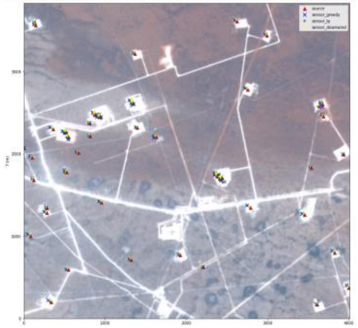
Historical methane leaks distribution

Forward methane dispersion simulation



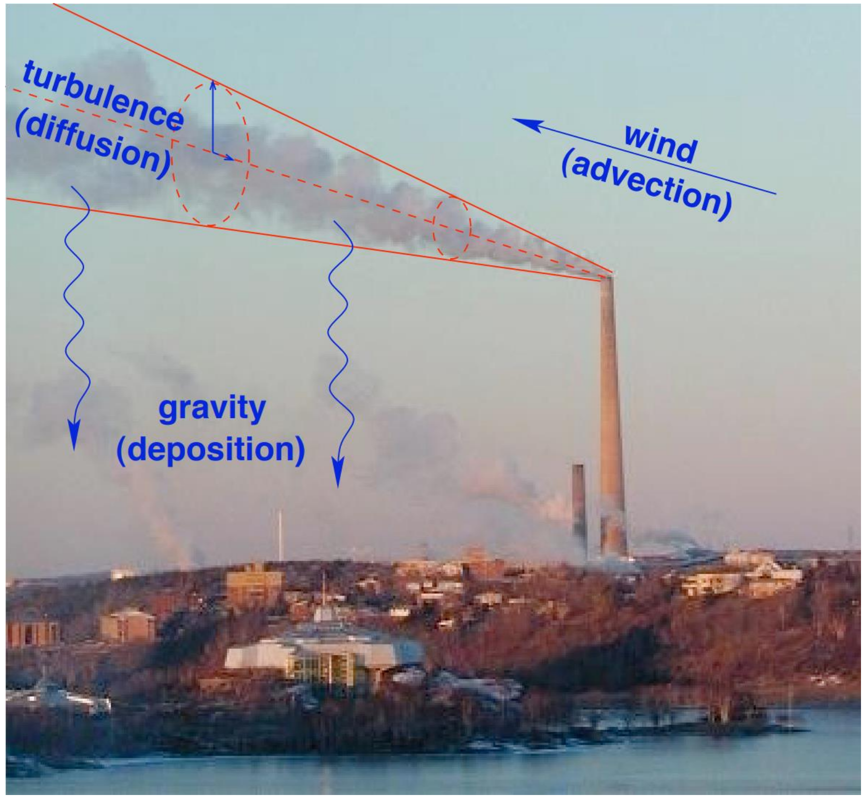
Ground sensor recordings

Invert for methane sources and leak rates



Data Ingestion → Methane Dispersion Modeling → Methane Source Attribution

Methane dispersion modeling



(From John Stockie)

3D advection-diffusion equation (2nd order PDE)

$$\frac{\partial C}{\partial t} + \nabla \cdot (C\vec{v}) = \nabla \cdot (D\nabla C) + S$$

S: methane leak source

$\vec{v}(x,t)$: wind velocity field

D: diffusion coefficient matrix

PDE inputs

Physics-based numerical solver

Deep-learning-based proxy modeling

$C(x,t)$: methane concentration field

PDE output

FNO training data generation with cloud HPC

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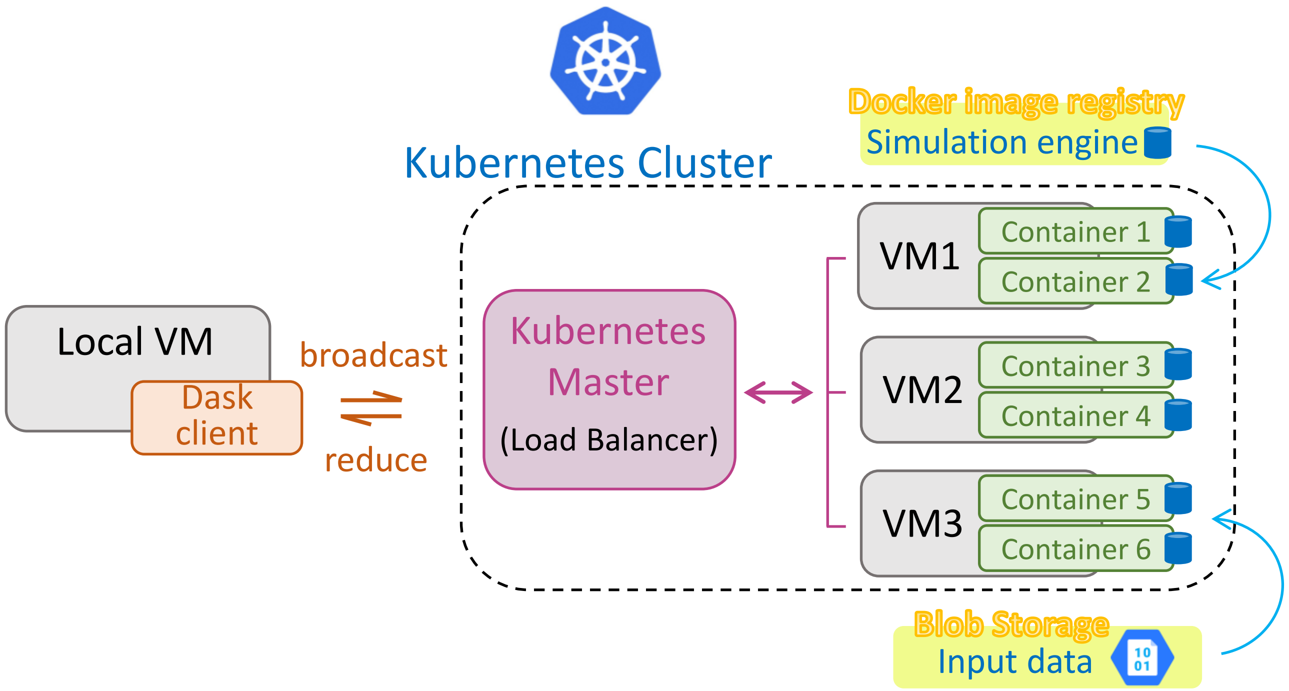
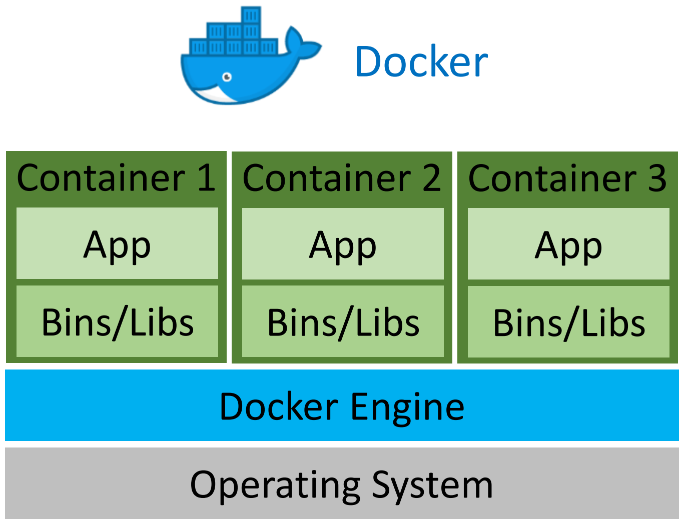
Cloud HPC to generate input/output pairs of 3D methane dispersion PDE using physics-based numerical solver

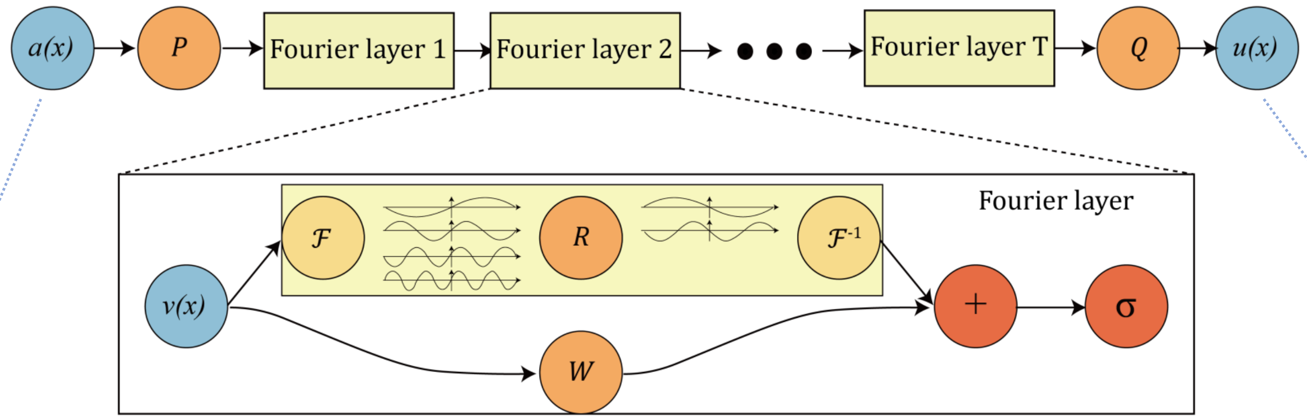
- Cloud-native HPC: Dask + Kubernetes containers (on Azure) (https://library.seg.org/doi/10.1190/segam2021-3594908.1)
- Advantages: Scalability, fault-tolerance, auto-scaling, and spot VMs
- Ease of use: Minimal code change for switching to HPC





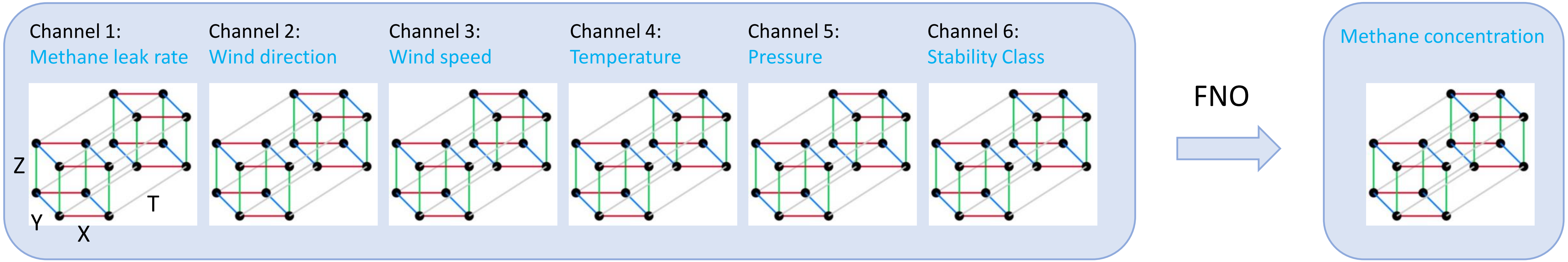
Fourier Neural Operator (FNO) surrogate modeling

FNO architecture
(Li et al., ICLR 2021)



Challenges for our study:
(1) Time-variant inputs
(2) 3D PDEs, 4D FFT for FNO
(3) FNO model: ~150m parameters

FNO for 3D methane dispersion modeling

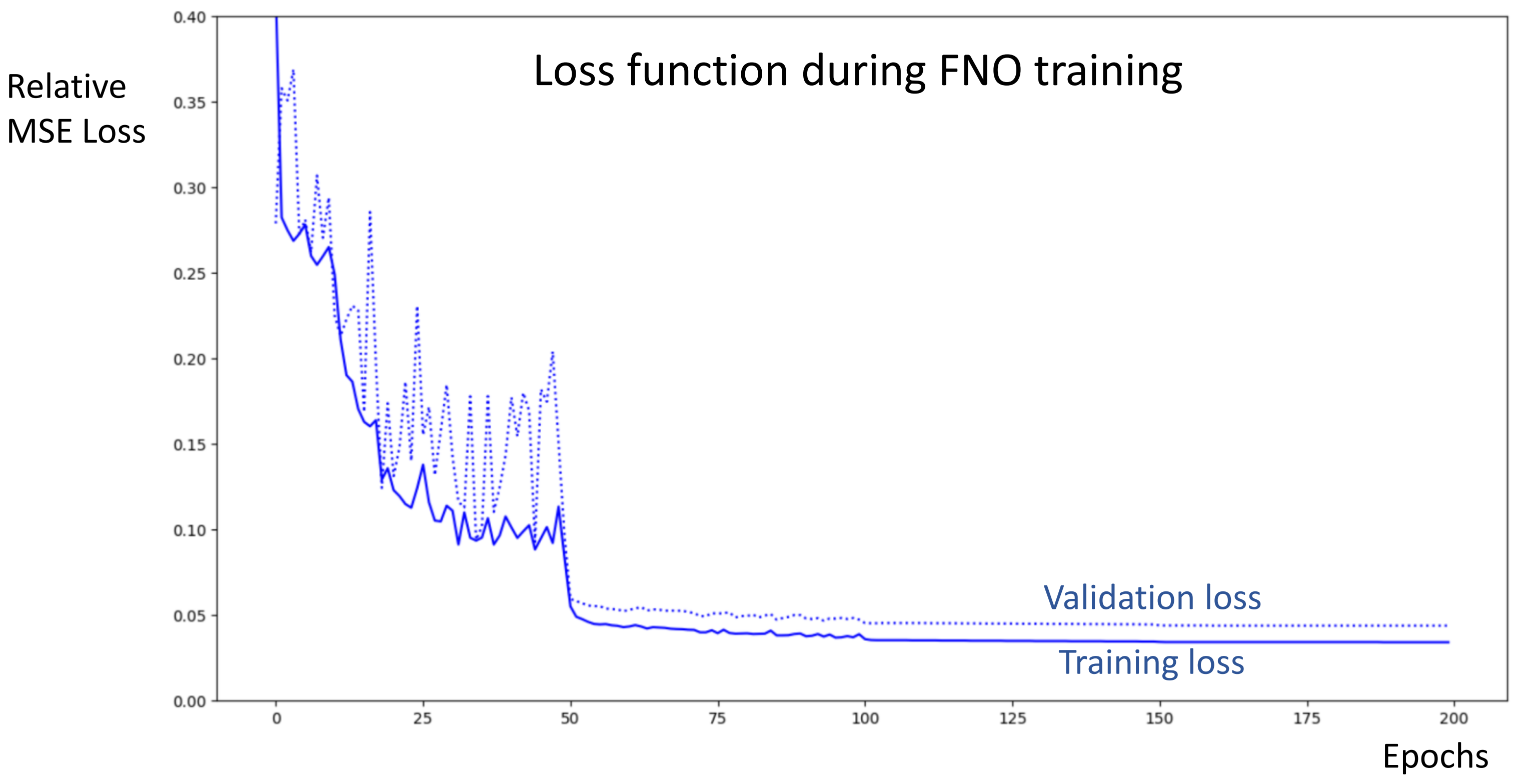


Input (X, Y, Z, T=24, C=6): based on historical weather data

Output (X, Y, Z, T=24, C=1)

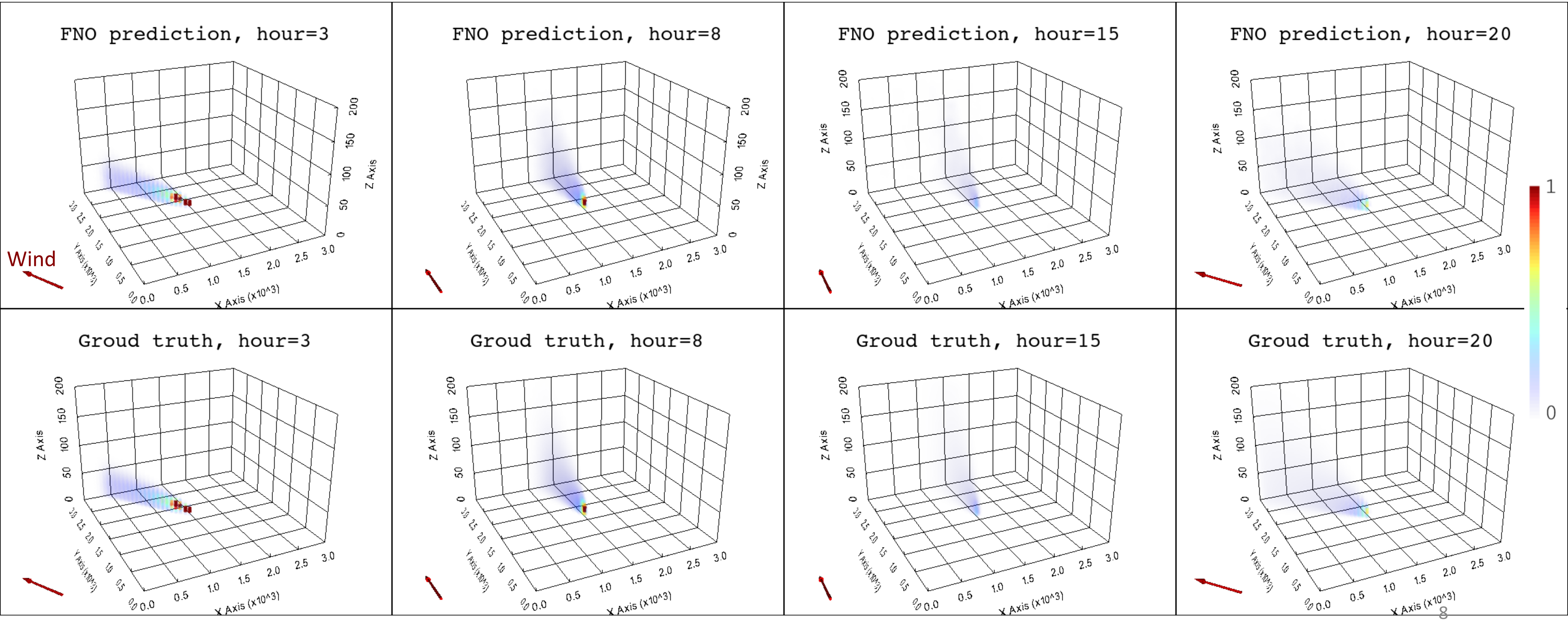
FNO training

- FNO model training using 4800 samples (4000 for training, 800 for validation)
- Use Adam optimizer with learning rate decay
- ~150 million parameters in our FNO model for learning 3D dispersion operator
- Distributed training (8 Nvidia V100 GPUs) with DeepSpeed (https://github.com/microsoft/DeepSpeed)



FNO proxy model results for 3D methane dispersion

- FNO emulates the highly non-linear PDE solver (3D dispersion) very well
- FNO is capable of handing rapid changes of wind over time
- Inference time << 1 sec, where 24 time-steps (24 hours) are predicted in one inference



Conclusions

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- Methane leak detection and remediation are critical for tackling climate change, where methane dispersion simulations play an important role in emission source attribution.
- As 3D modeling of methane dispersion is often costly and time-consuming, we train a deep-learning-based surrogate model using the Fourier Neural Operator (FNO) to learn the PDE solver in our study.
- Our result shows that our FNO surrogate modeling provides a fast, accurate and cost-effective solution to methane dispersion simulations, thus reducing the cycle time of methane leak detection.