

Efficient generation of native resolution NO₂ a priori profiles for TEMPO retrievals using machine learning

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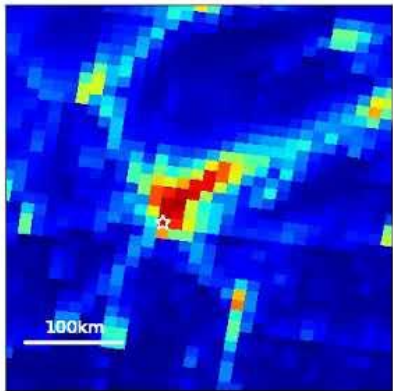
Qindan Zhu

Hannah Kenagy

Ron Cohen

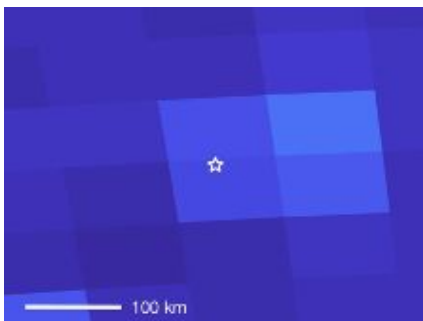
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Accurately interpreting TEMPO NO₂ observations requires *a priori* profiles at both high spatial and high temporal resolution

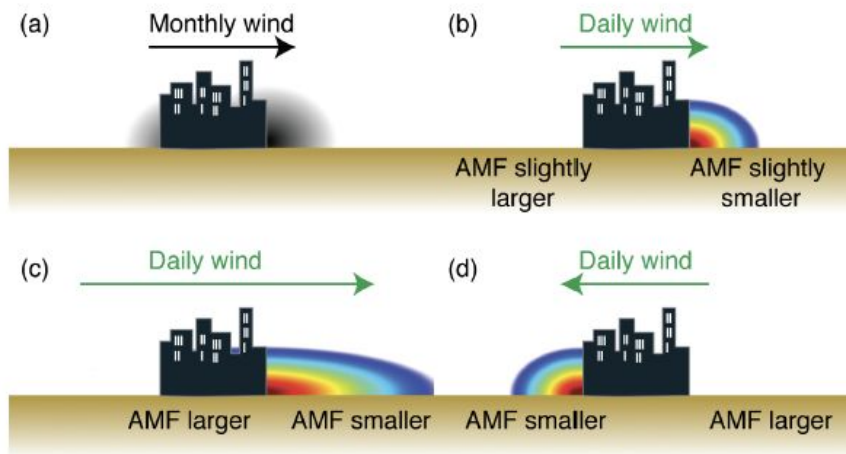


BEHR (BERkeley High spatial resolution OMI satellite NO₂ Retrievals) product uses daily modeled *a priori* profiles at 12 km x 12 km to capture the daily variation in AMF.

NASA OMI operational product v4.0 utilizes 1 deg x 1.25 deg GMI model based monthly *a priori* NO₂ profile shapes.

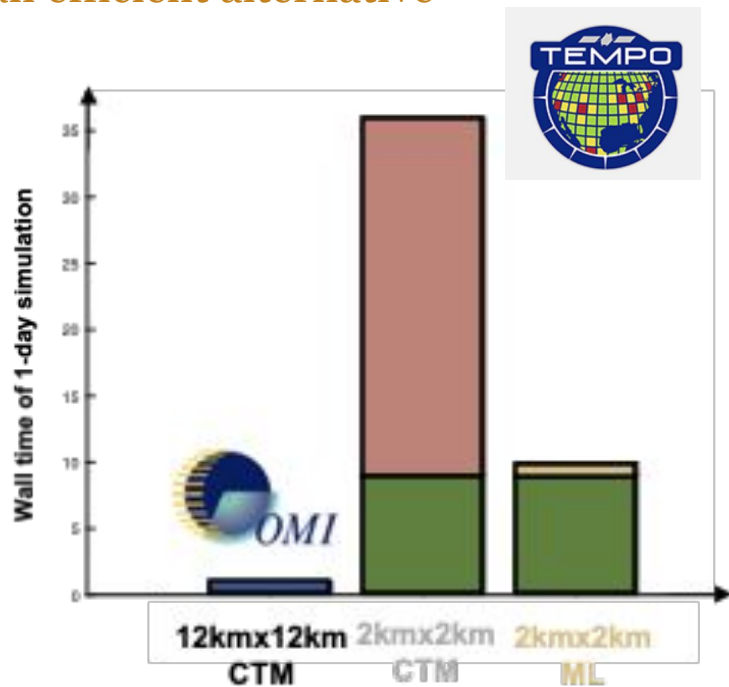


The *a priori* NO₂ profiles are the largest contributor to uncertainty in satellite retrievals. Incorrect profiles lead to systematic biases in estimating NO_x lifetime and emissions from satellite retrievals.

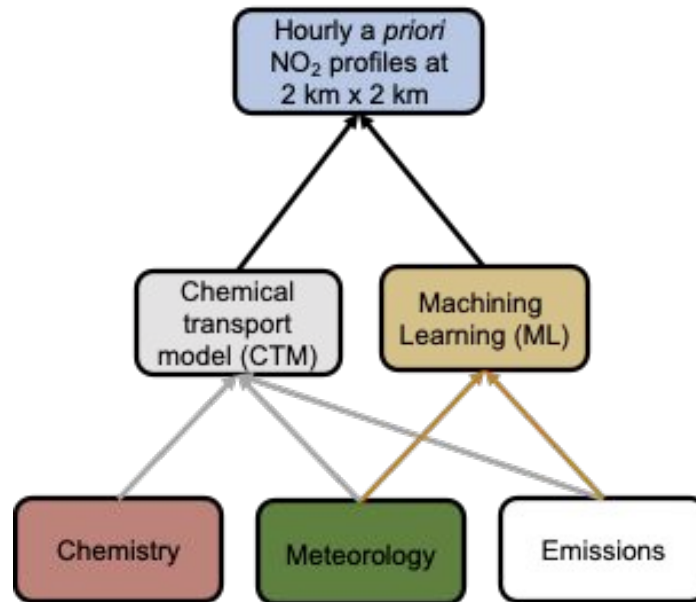


Schematic from Laughner et al., 2016. (a) Monthly average *a priori* profiles. (b) A case when the daily wind is similar to the monthly average wind. (c) A case where the daily wind is significantly faster than the average but blows in the same direction. (d) A case where the daily wind direction is different from the monthly average.

Chemical transport model (CTM) is computationally expensive: Machine learning (ML) is an efficient alternative



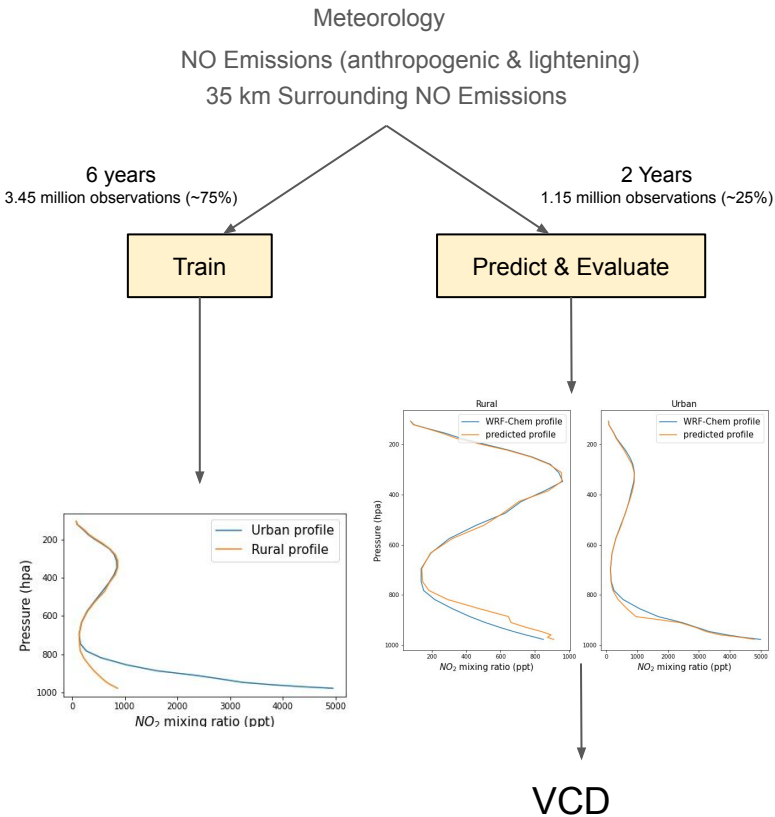
Back-of-the-envelope estimate of computation time running WRF-Chem on 12 nodes (Skylake processor (2x16 @ 2.1 GHz) 96 GB RAM, 32 cores per node, Berkeley High Performance Computing) for CONUS.



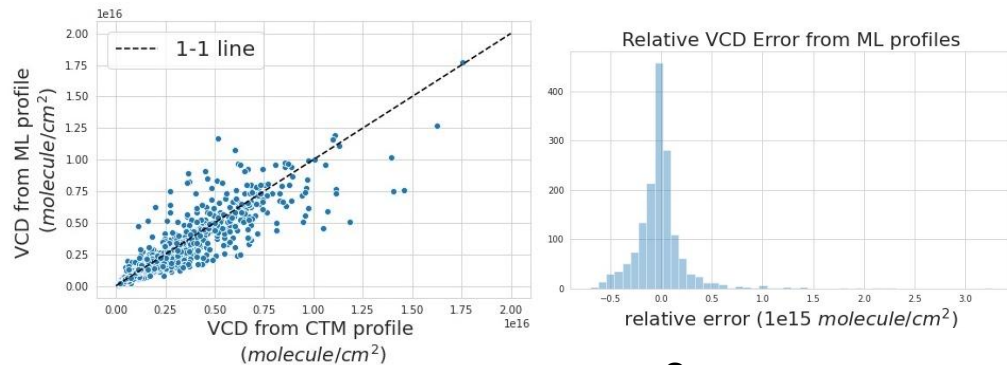
Goal: produce NO_2 *a priori* profiles at native TEMPO resolution using **machine learning on meteorological forecast/analysis and a high resolution emissions inventory**.

Case Study - Atlanta, GA, USA

Method



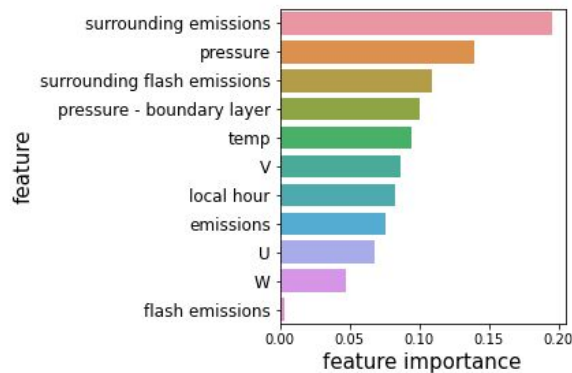
Results



Summary

Machine learning is a computationally efficient method for producing NO₂ vertical profiles at native TEMPO resolution in **real time**.

Our model is generalizable because it can capture variability of urban and rural domain

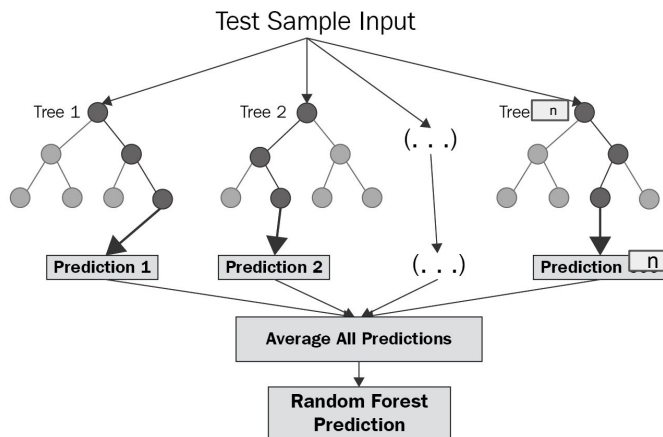


Future Work/Next Steps

Scale up to CONUS - 13.8 billion observations/year!

Supplement

Random Forest Ensemble



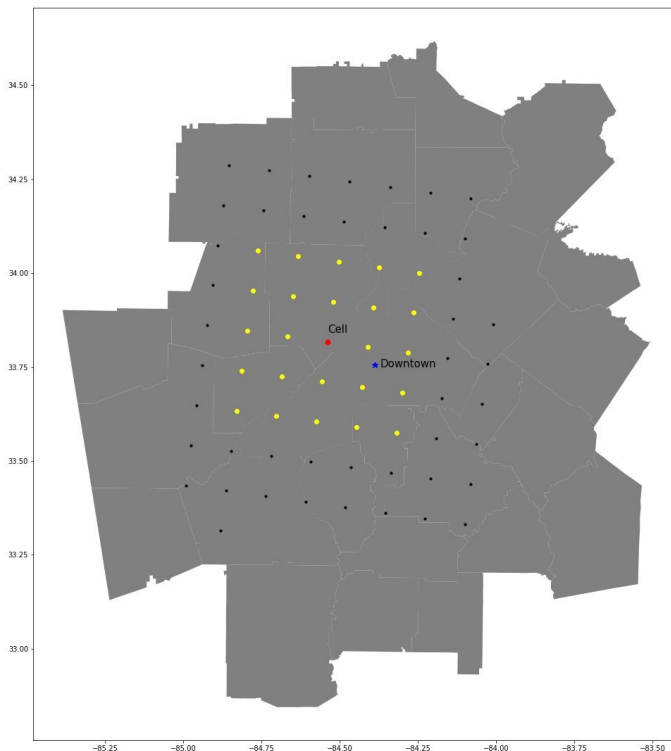
<https://towardsdatascience.com/random-forest-and-its-implementation-71824ced454f>

Library



Parameters

Num trees: 100
Criterion for split: MSE
Max features: 10
Bootstrap: True



Range of Data

<u>Years:</u>	<u>Vertical Layers:</u>
2005	29
2007-2009	
2011-2014	<u>Geo Coordinates</u>
<u>Month:</u>	<u>Urban Dataset:</u>
July	Lon [-85, -84]
	Lat [33.3, 34.3]
<u>Time:</u>	<u>Rural Dataset:</u>
5am - 5pm	Lon [-84, -86]
(SZA < 80°)	Lat [33, 34]
Hourly	

List of features

Each Observation:
Local Hour
Pressure
Temperature
U, V, W
Flash Emissions
(CG & IC)
Pressure - PBL
NO Emissions

Surrounding Features:
35km Flash Emissions
(CG & IC)
35km NO Emissions