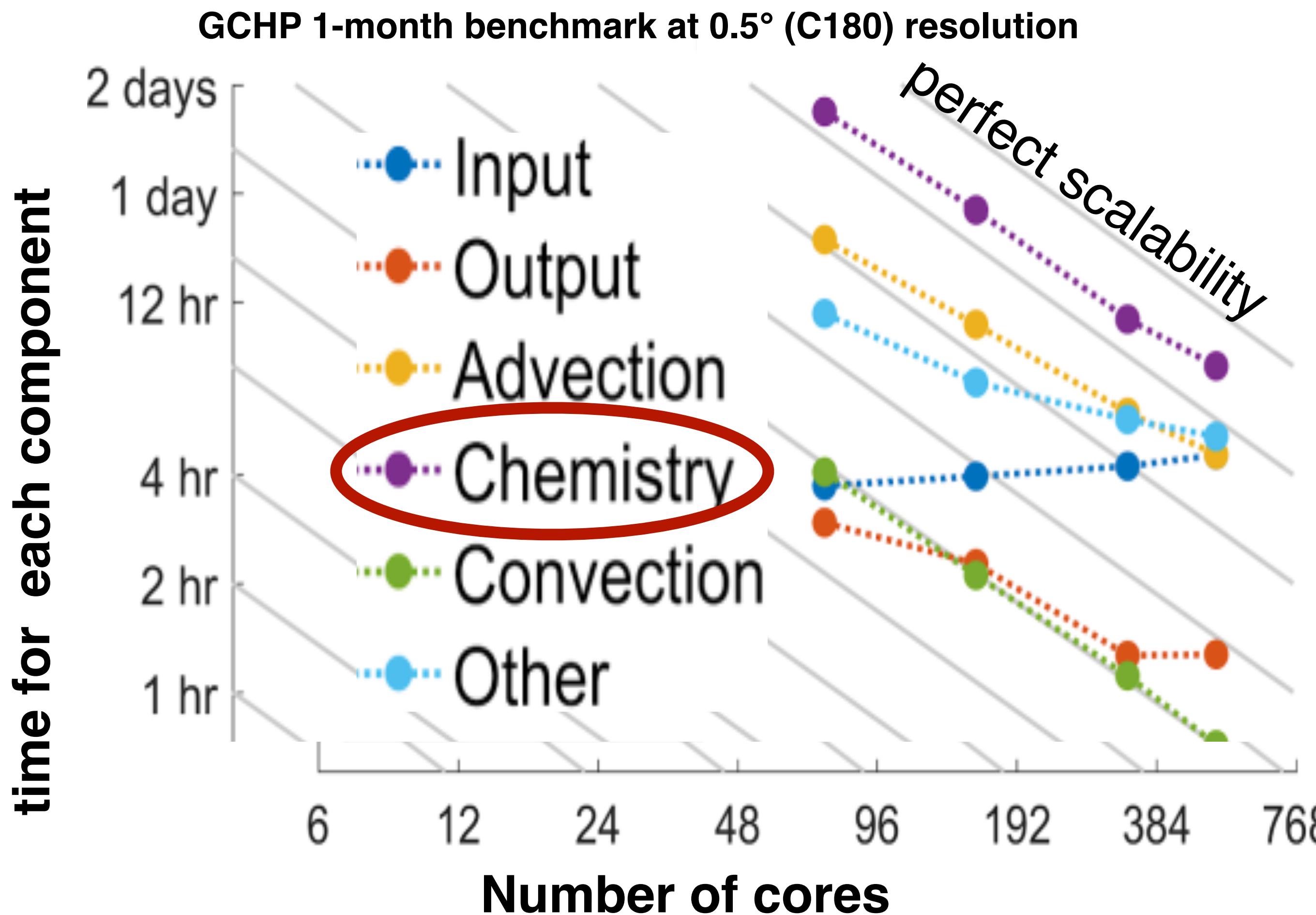


# An online-learned neural network chemical solver for stable long-term global simulations of atmospheric chemistry in S2S applications

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with Daniel Jacob, Haipeng Lin, Melissa Sulprizio  
AMS 20220126



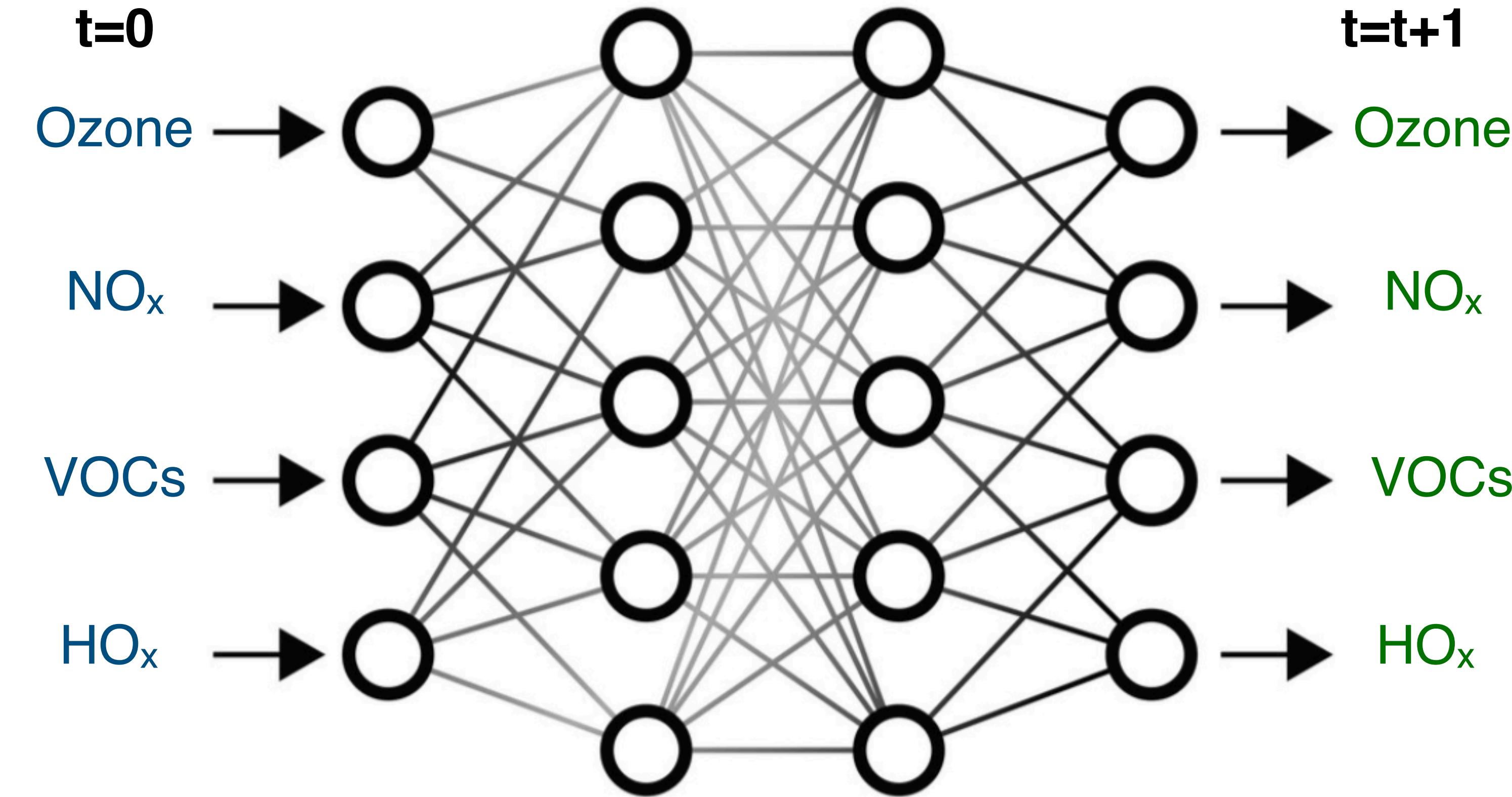
# Global modeling of atmospheric chemistry is a grand computational challenge



- Chemistry **dominates** the cost of a simulation (~40%) even though ideally scales
- Weather and climate models typically have **~4 variables**
- Chemistry models have **hundreds** of evolving species

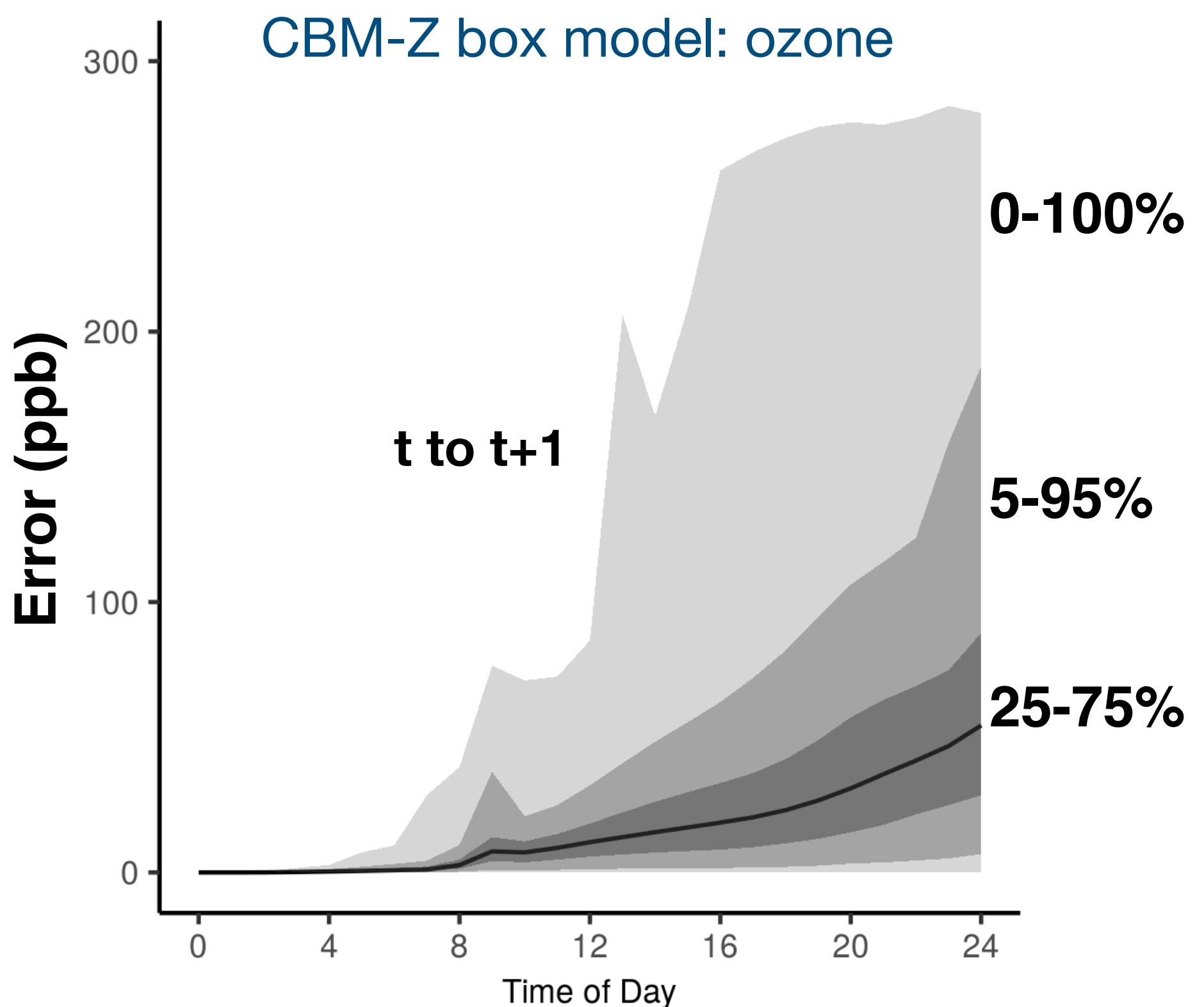
**Bottom Line:** Adding chemistry into an Earth system model becomes computationally infeasible

# Machine learning (ML) methods can provide a **solution** to this problem

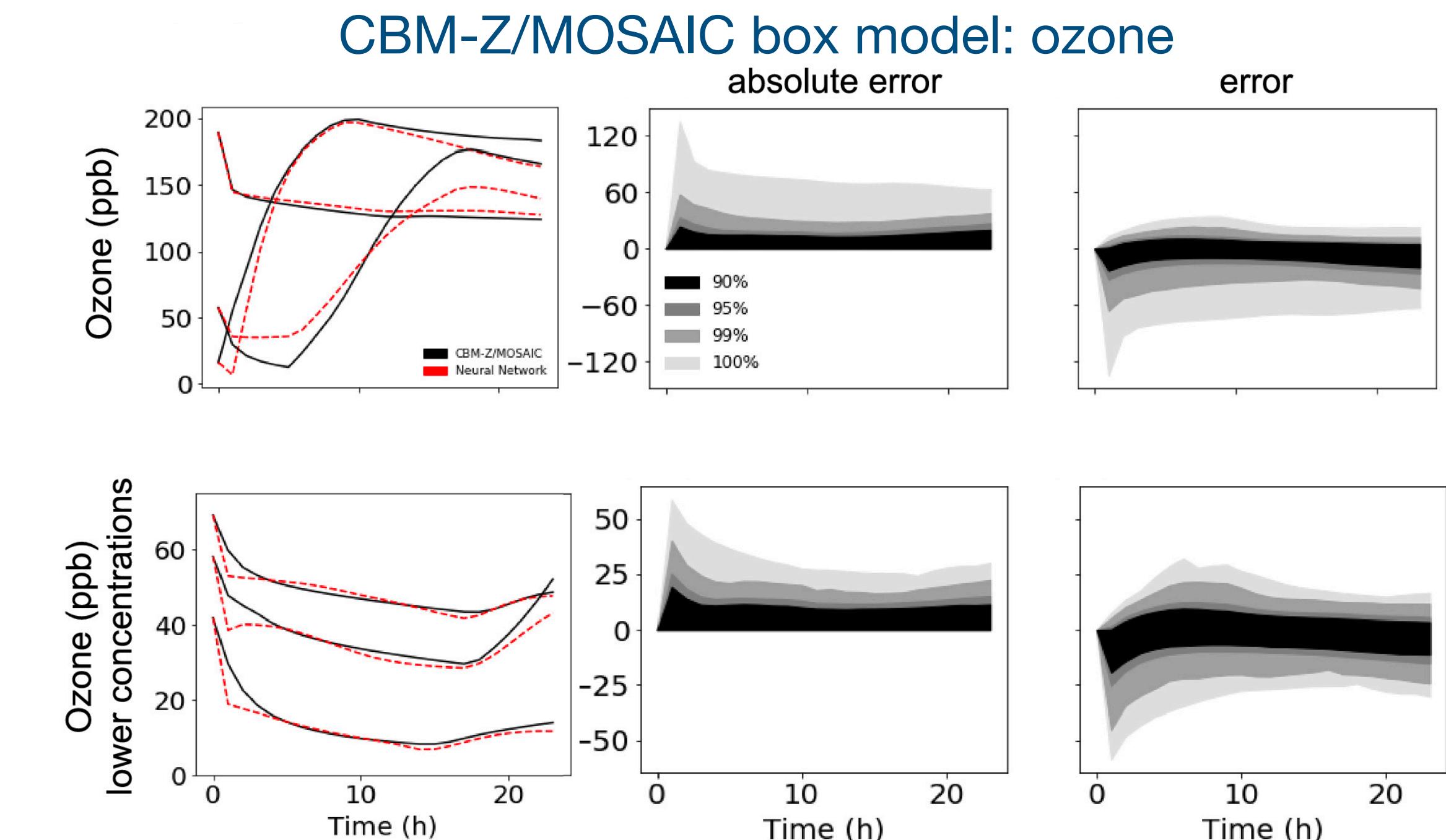
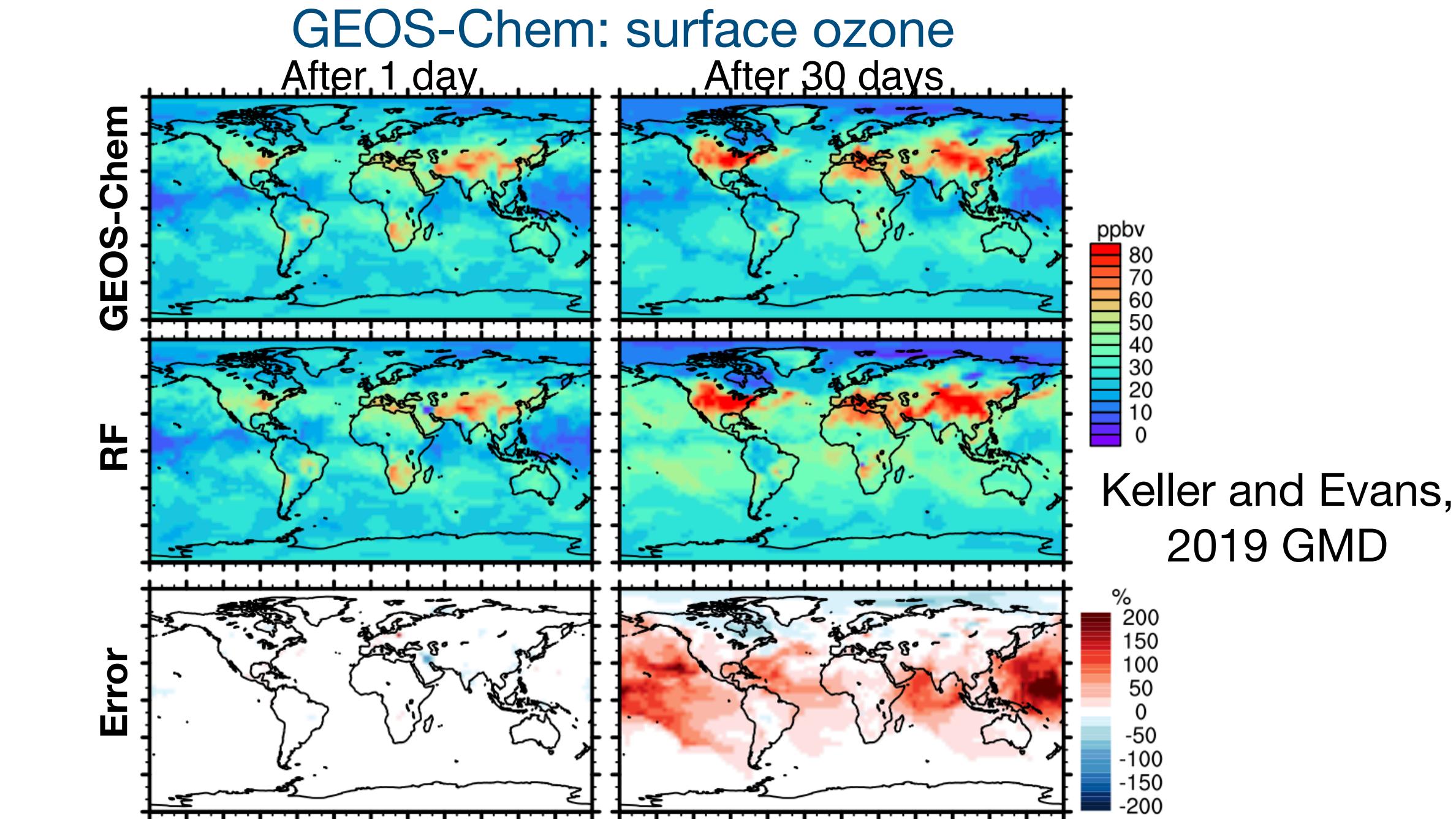


1. Nonparametric, **universal** function approximators
2. Learn to predict based on large dataset of **repeated** patterns
3. Proven to **speed up** solving ODEs at orders of magnitude (Malek and Shekari, 2006)

Past ML chemical solver attempts have encountered runaway error growth and have been limited to box model approaches

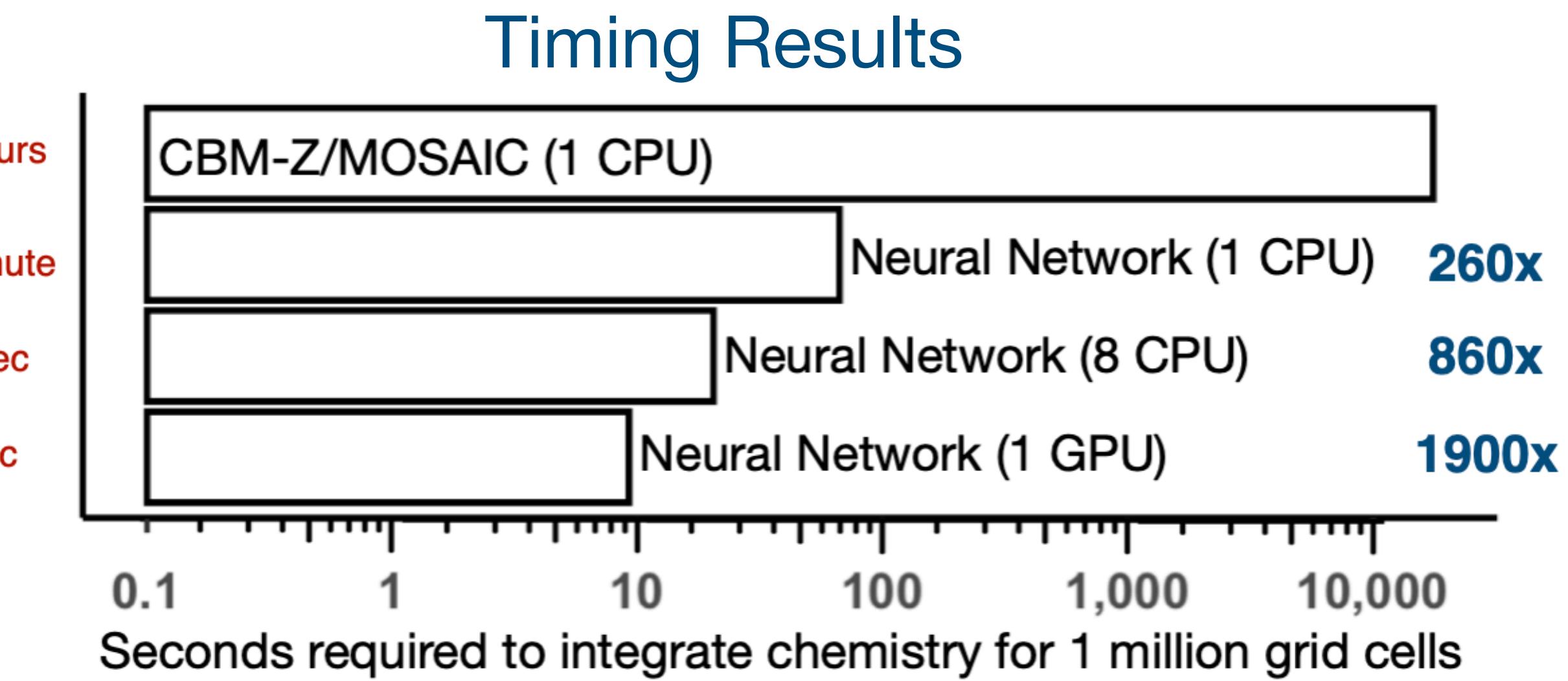
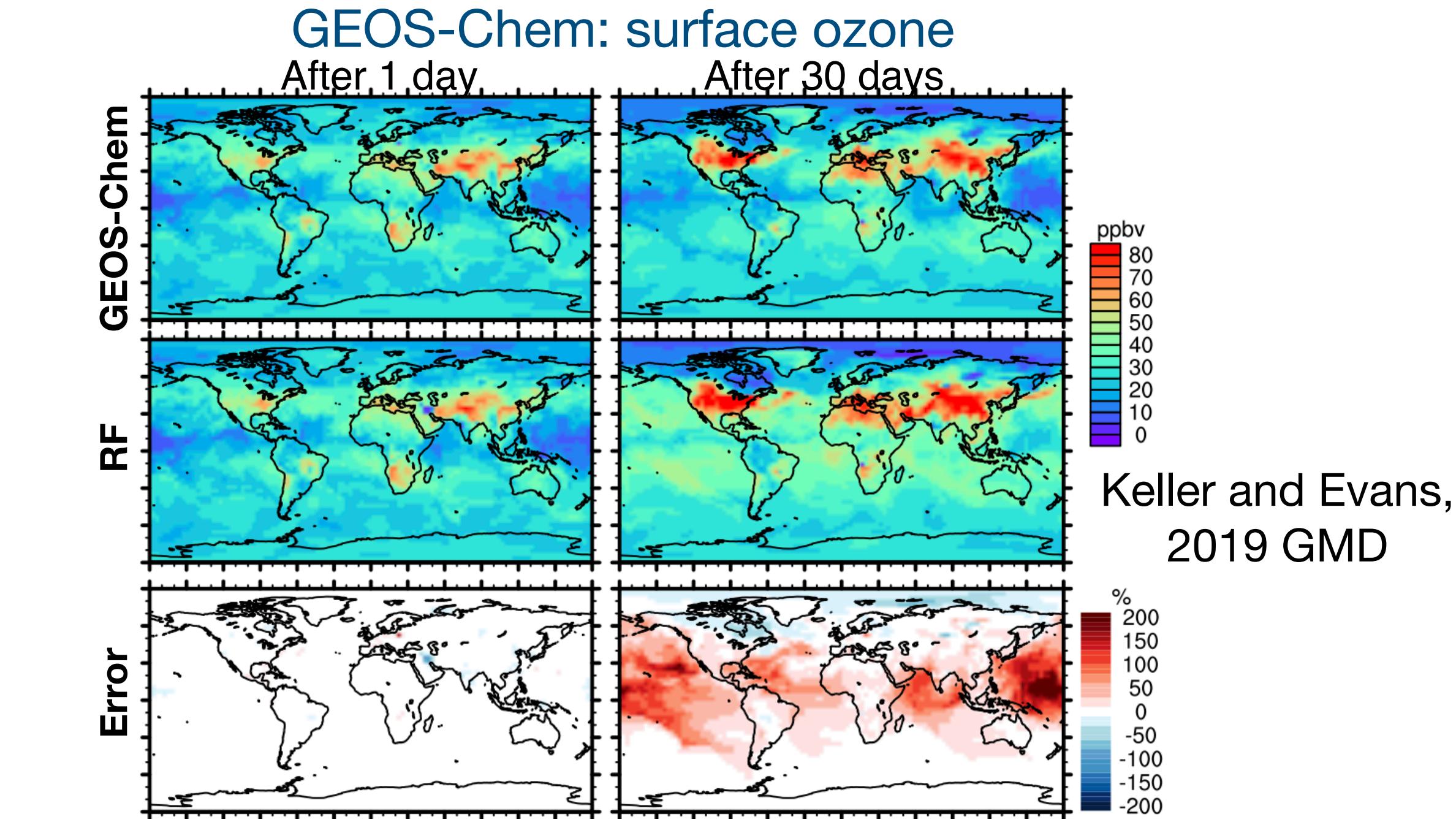
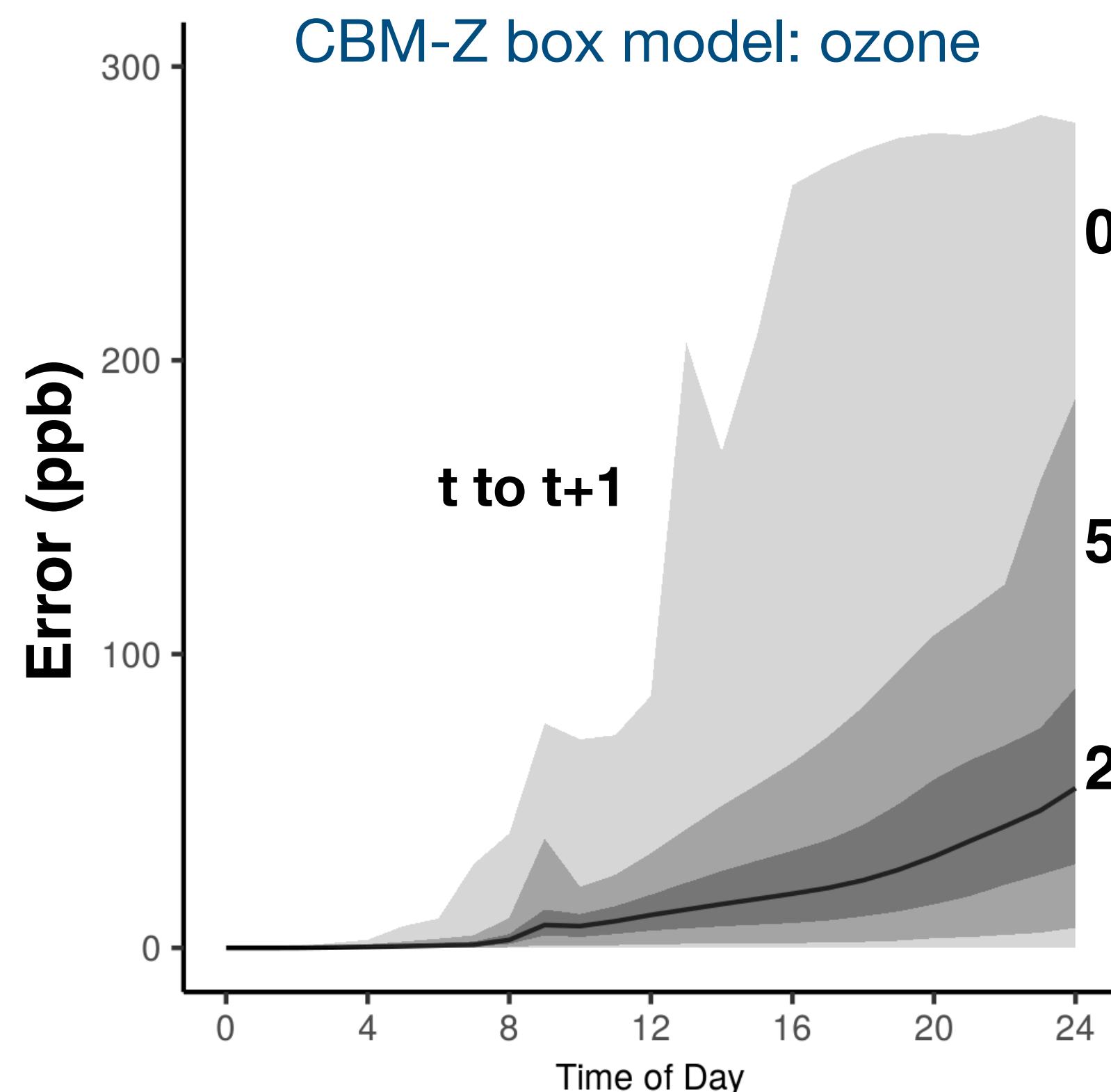


Kelp et al. 2018 ArXiv

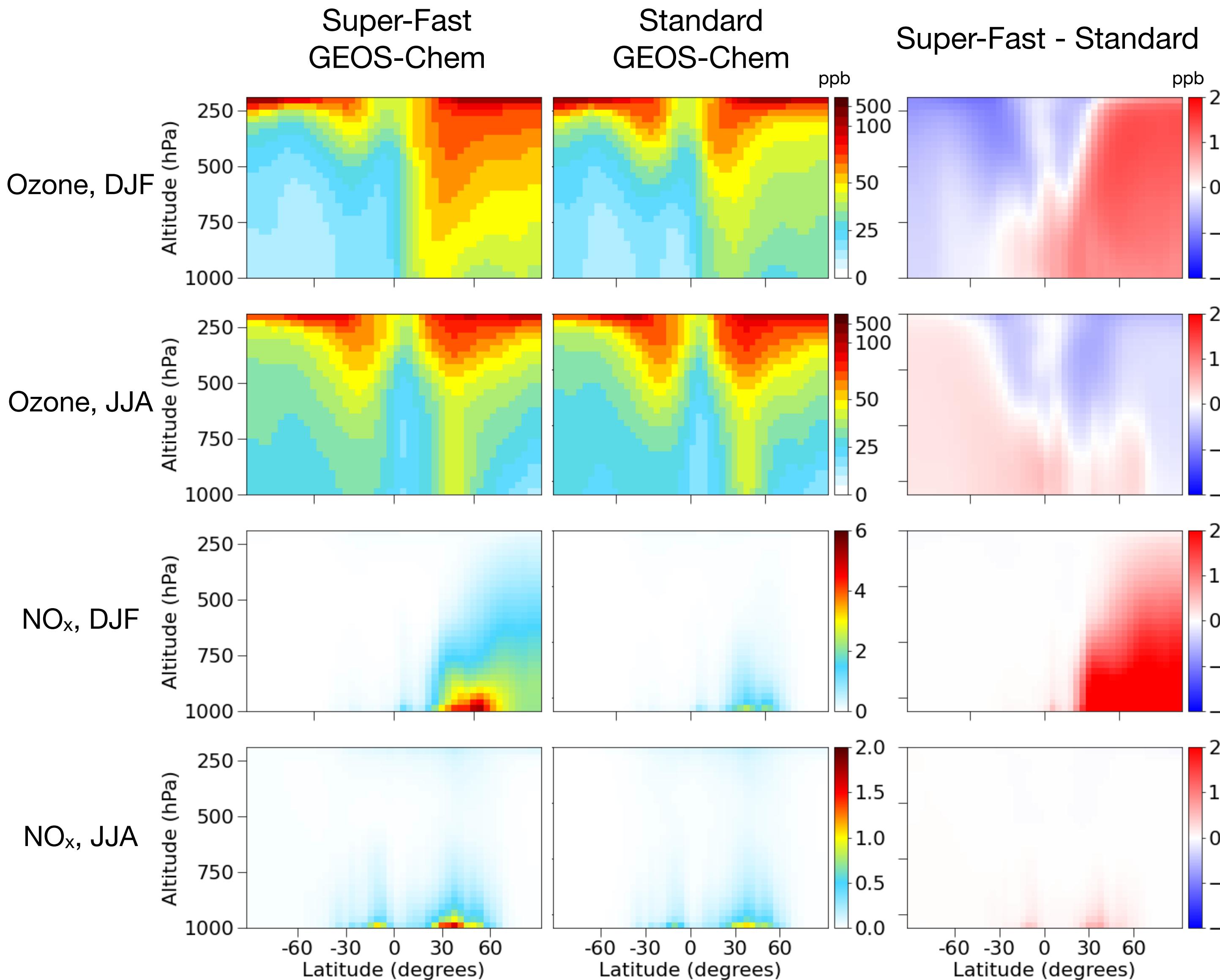


Kelp et al. 2020 JGR

Past ML chemical solver attempts have encountered runaway error growth and have been limited to box model approaches



# The ‘Super Fast’ chemical mechanism will allow us to better define ML methods and understand limitations in a full 3-D global modeling framework

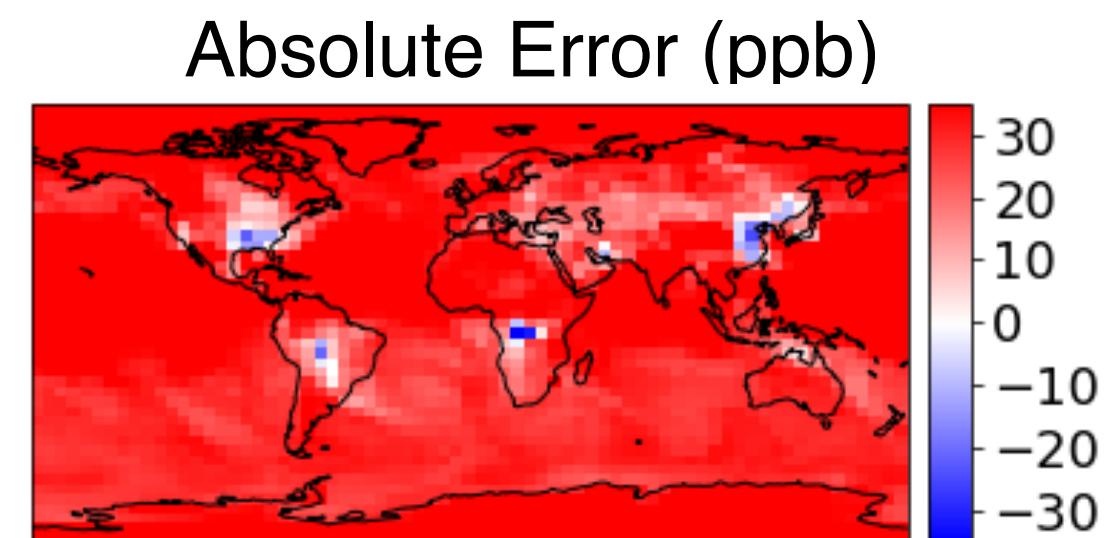


- Global mechanism with 12 species [Brown-Steiner et al., 2018]
  - Benchmarked in GEOS-Chem v12.0.0
  - 4x5° resolution
- 1-hour chemical time step output  
**20 variables:**  
2 physical var: T, air density  
6 photolysis frequencies  
12 gas-phase species  
1 month dataset would contain:  
 $\text{lon} \times \text{lat} \times \text{lev} \times \text{days} \times \text{hours} =$   
 $46 \times 72 \times \sim 25 \times 31 \times 24 \rightarrow \sim 62 \text{ million samples}$
- Training: 2016, Test: 2017**

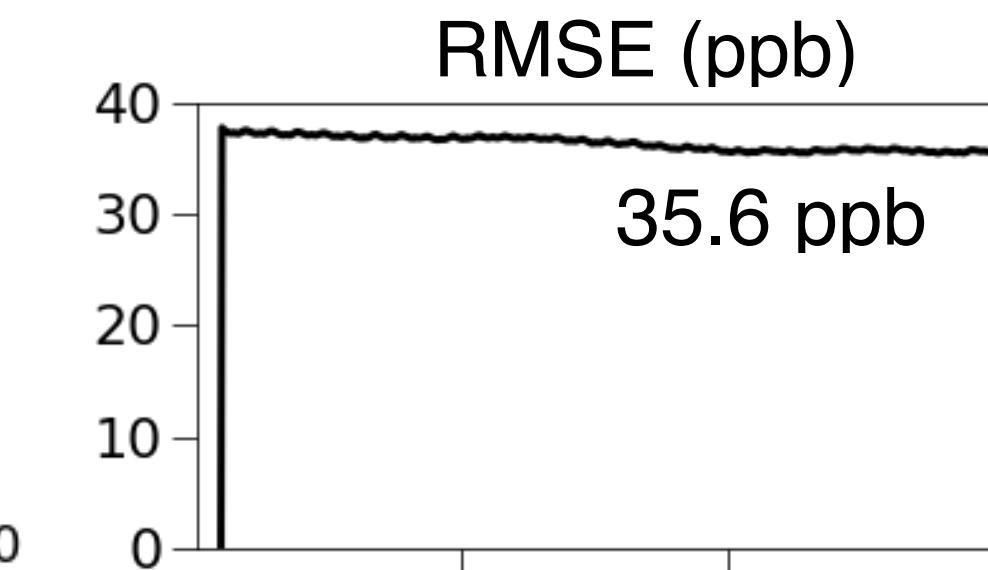
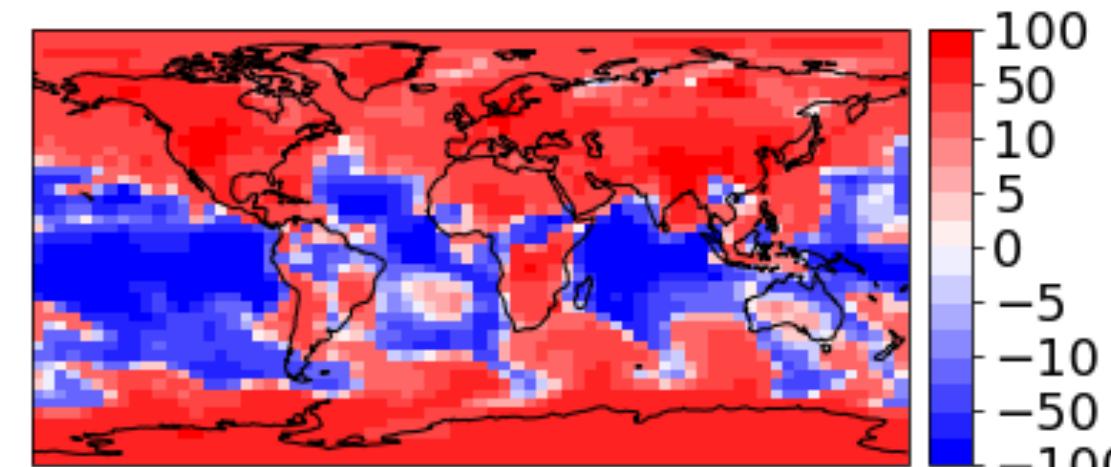
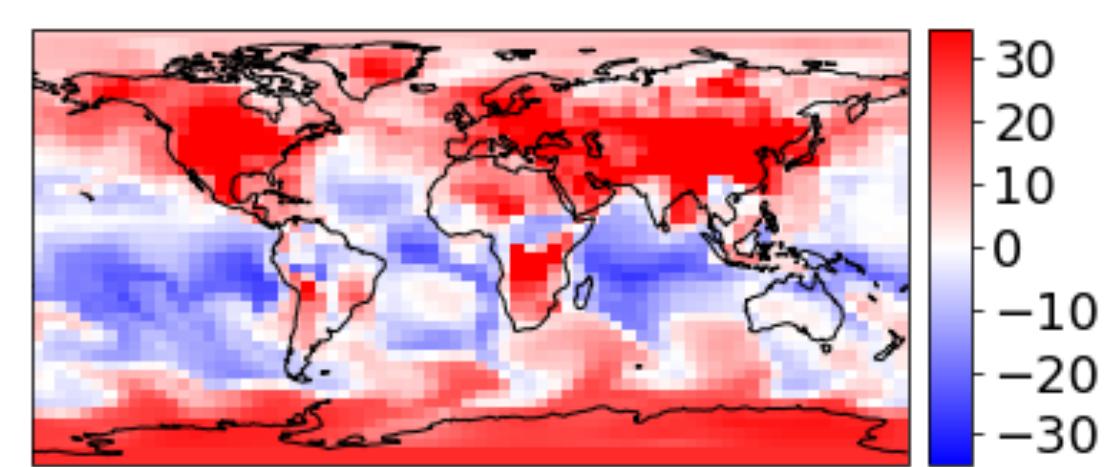
# Online training improves accuracy and stability over offline training

## Ozone

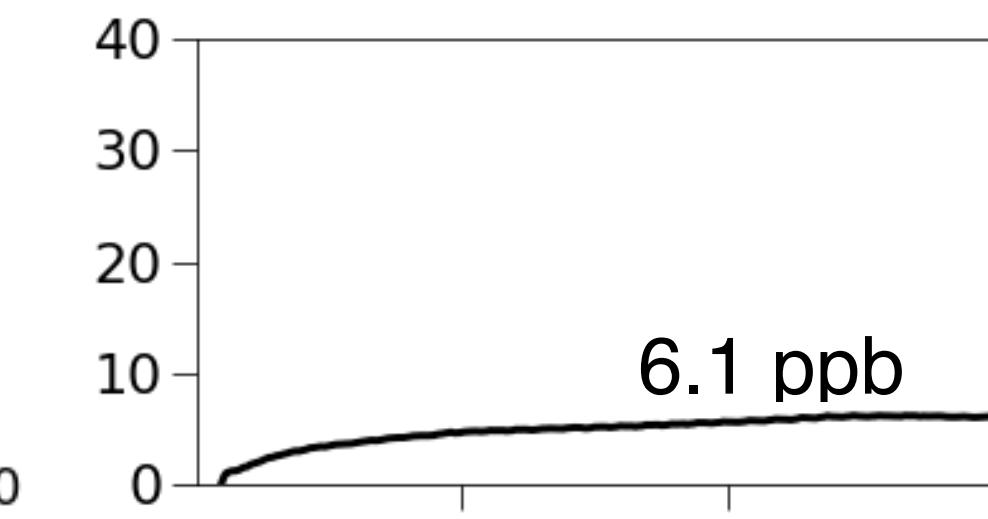
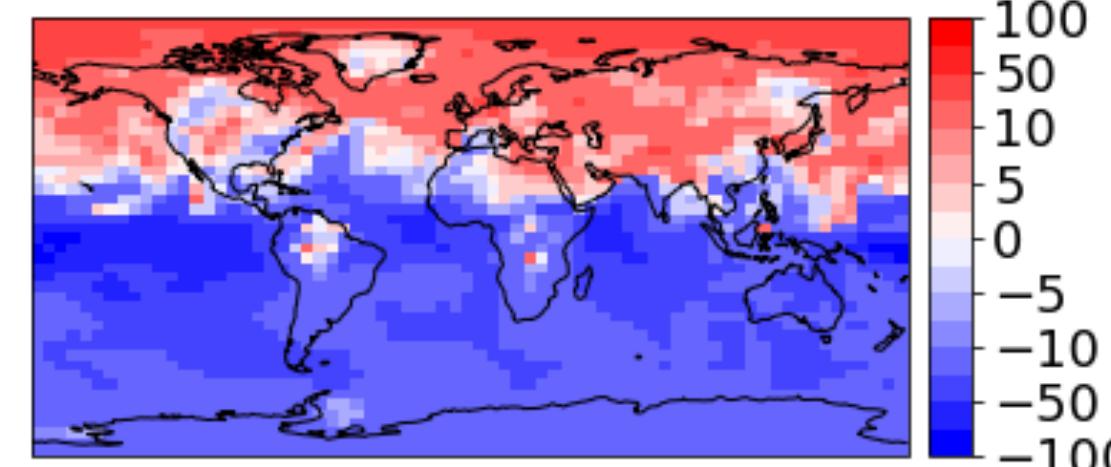
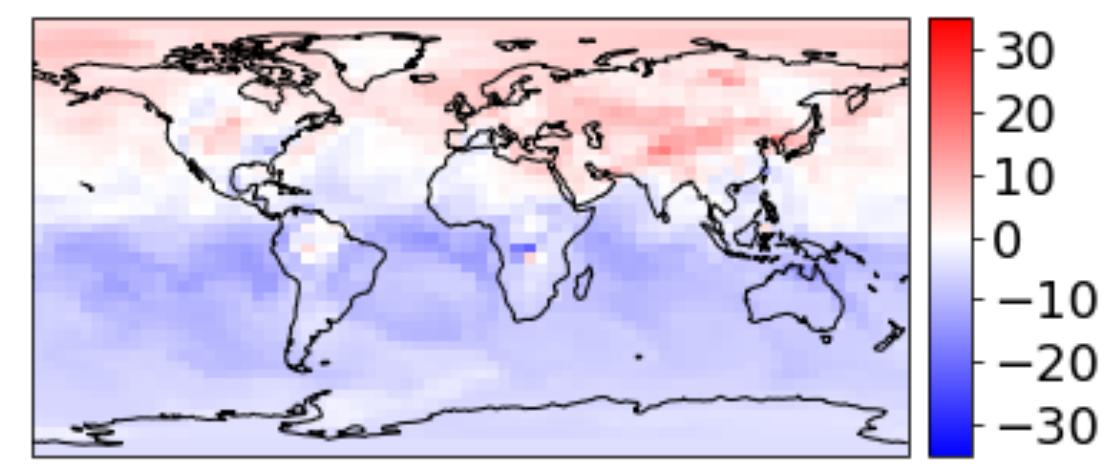
Offline  
 $t$  to  $t+1$



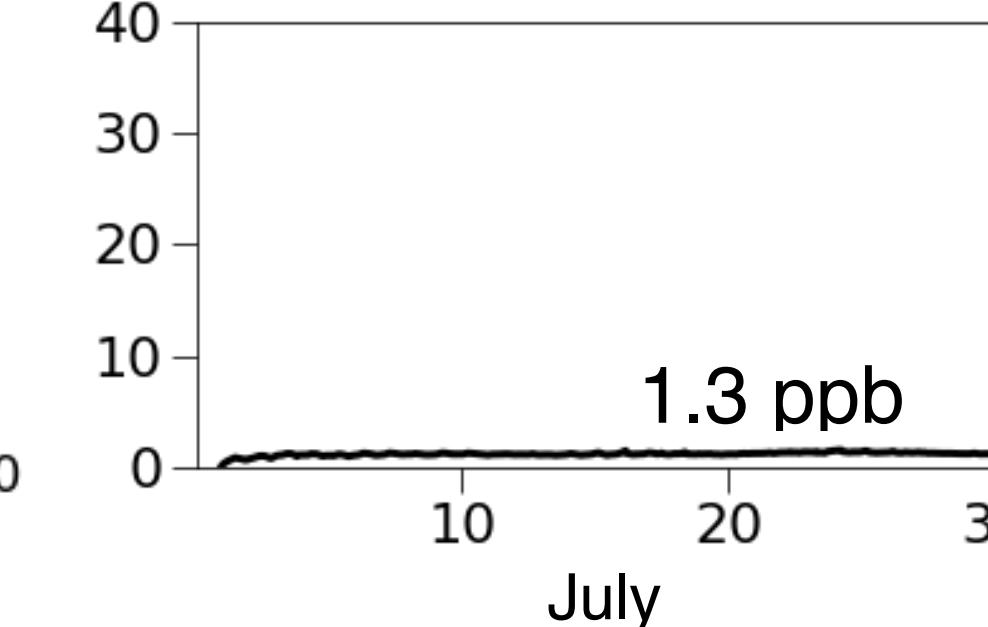
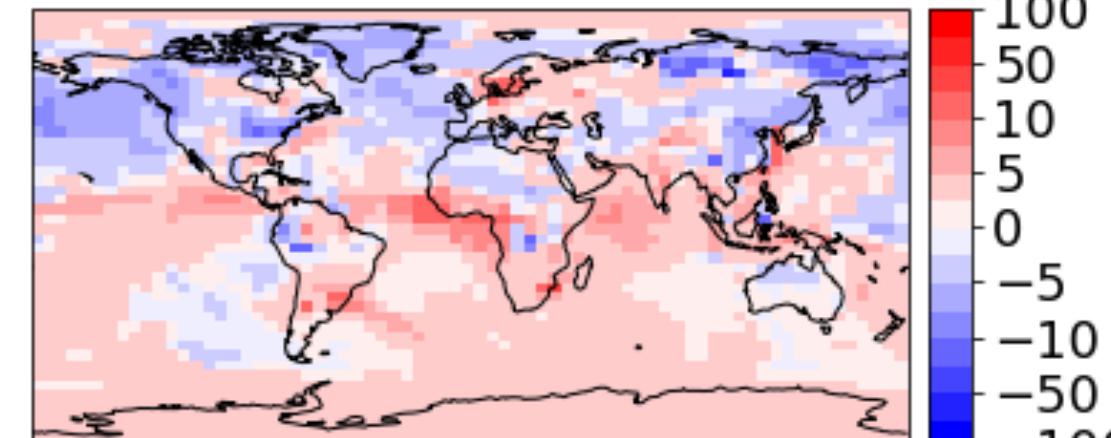
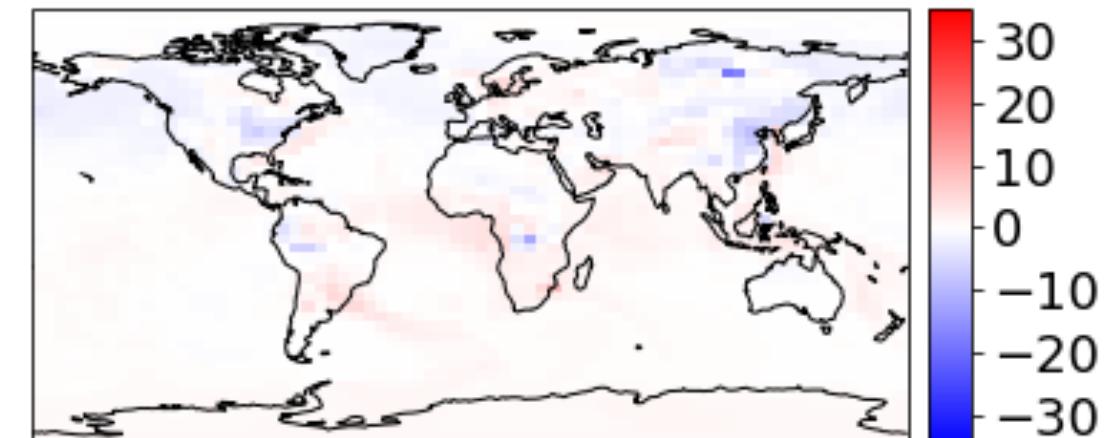
Offline  
24h recursive



Offline retrained  
to online



Online



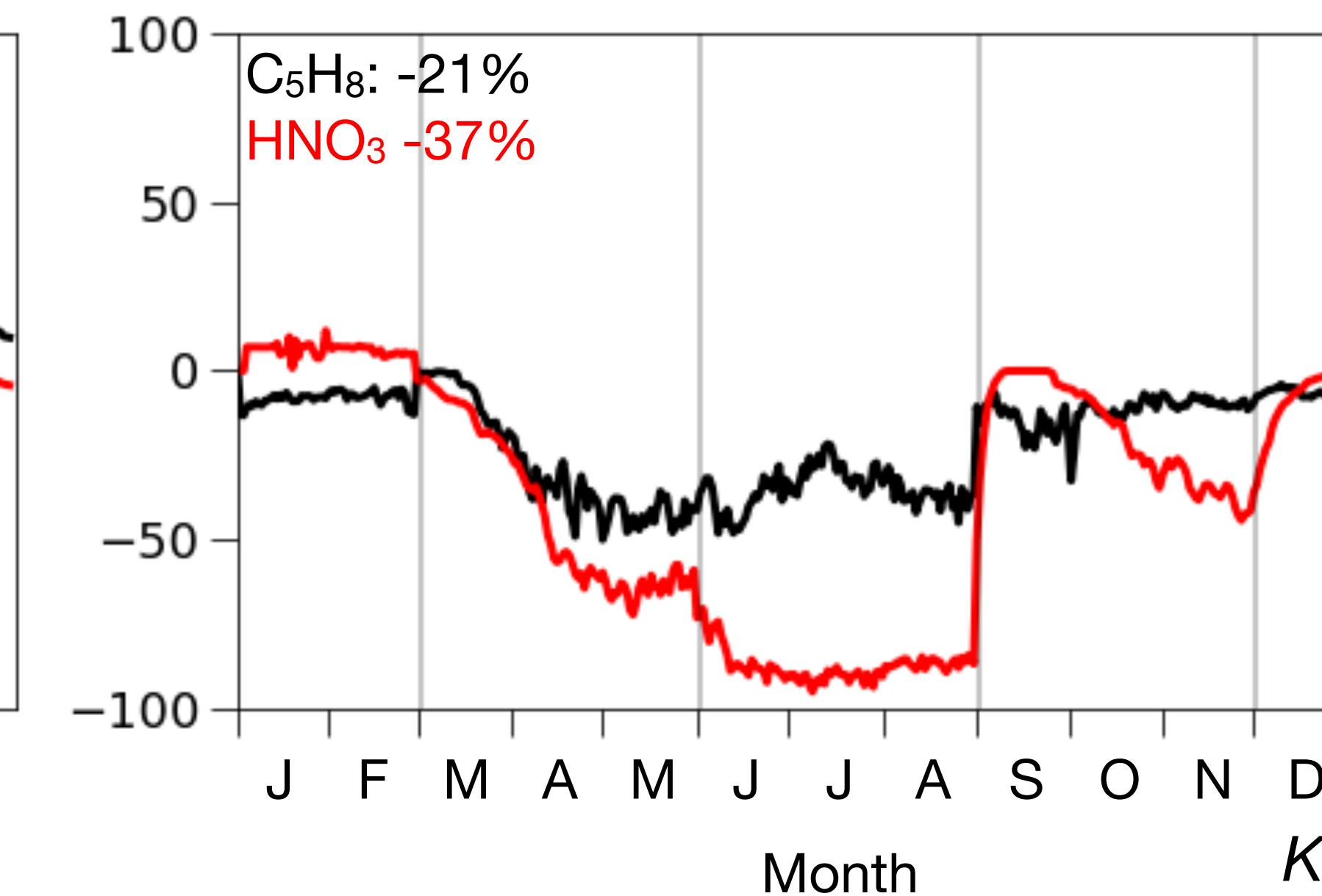
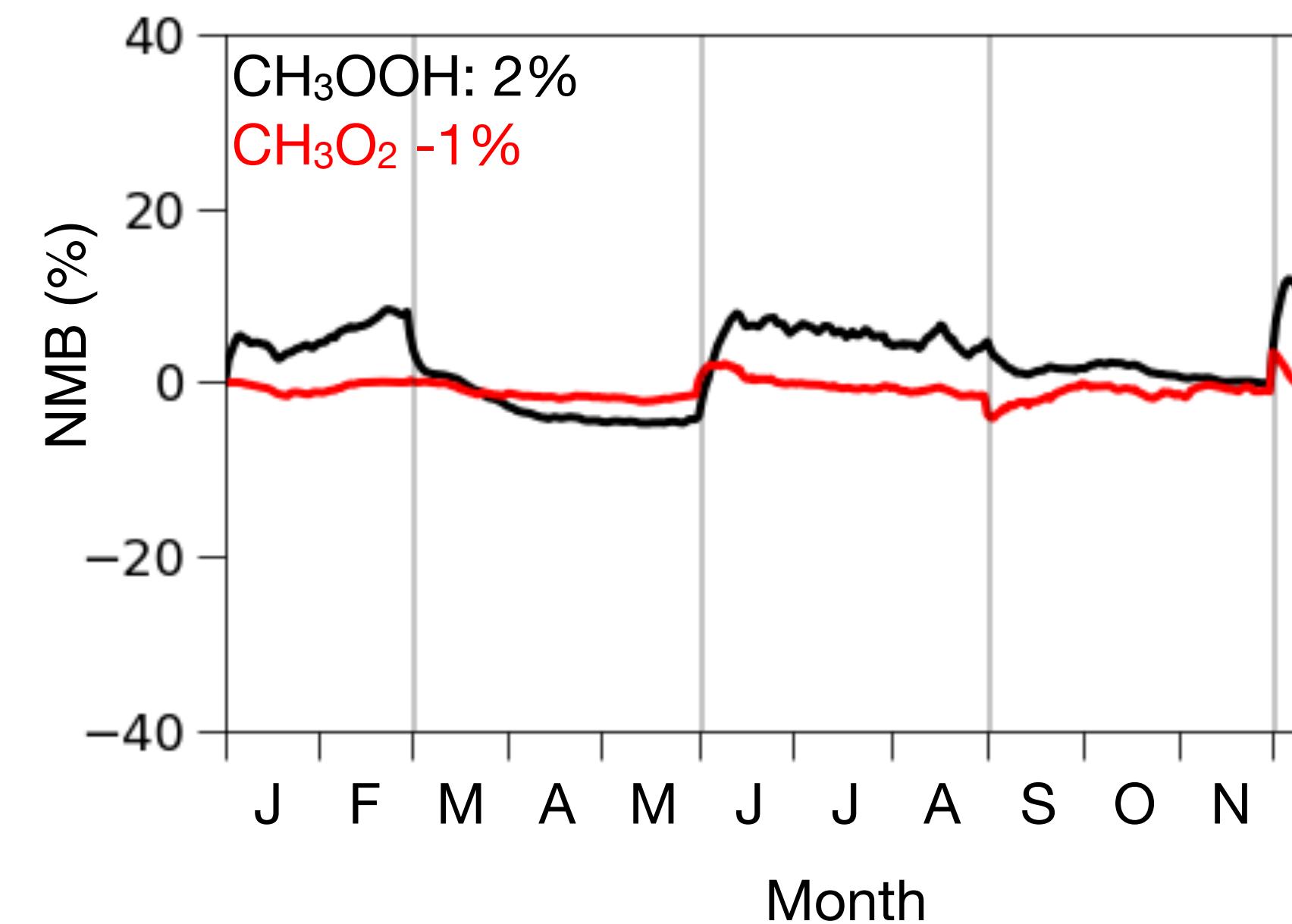
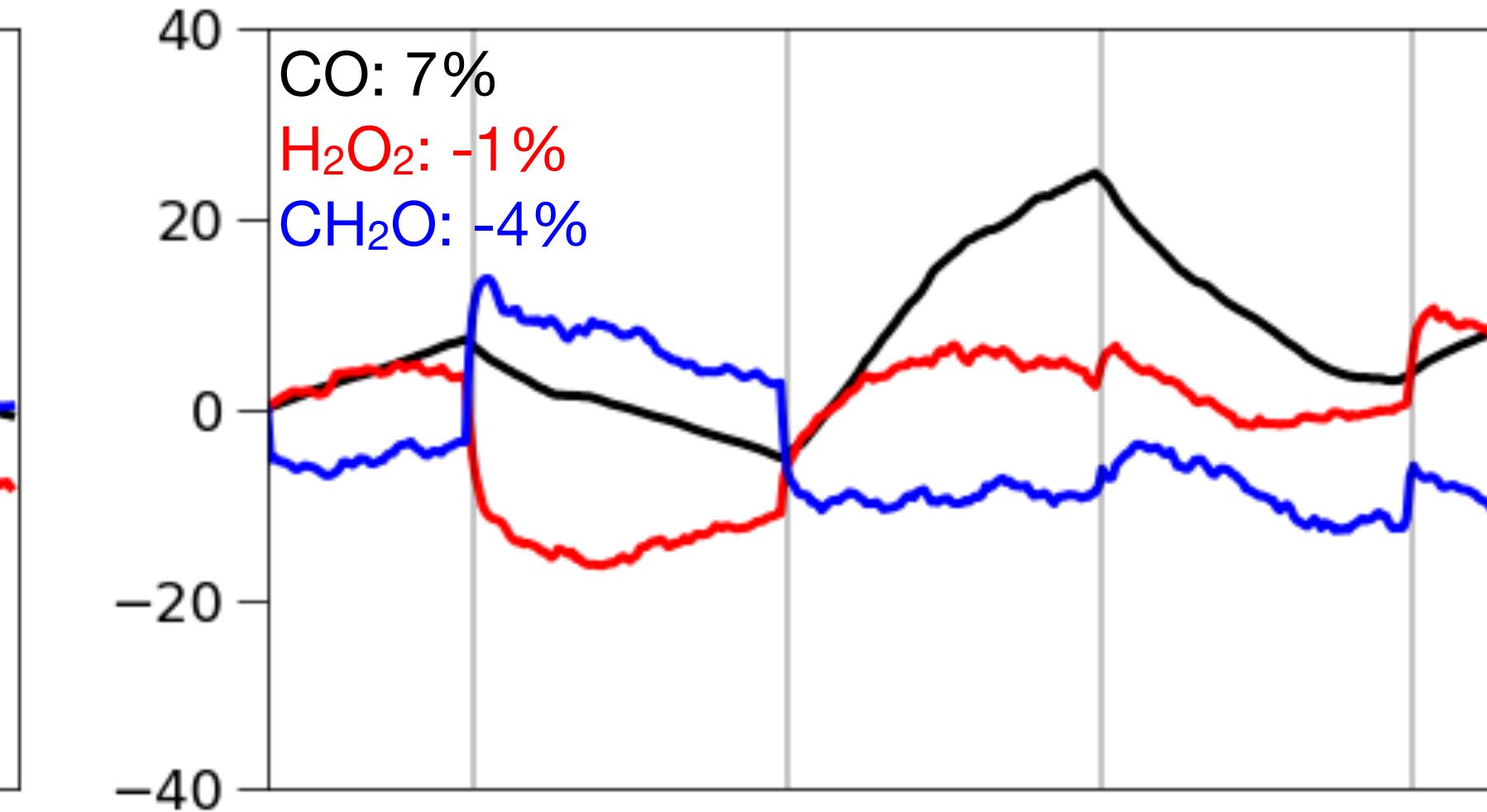
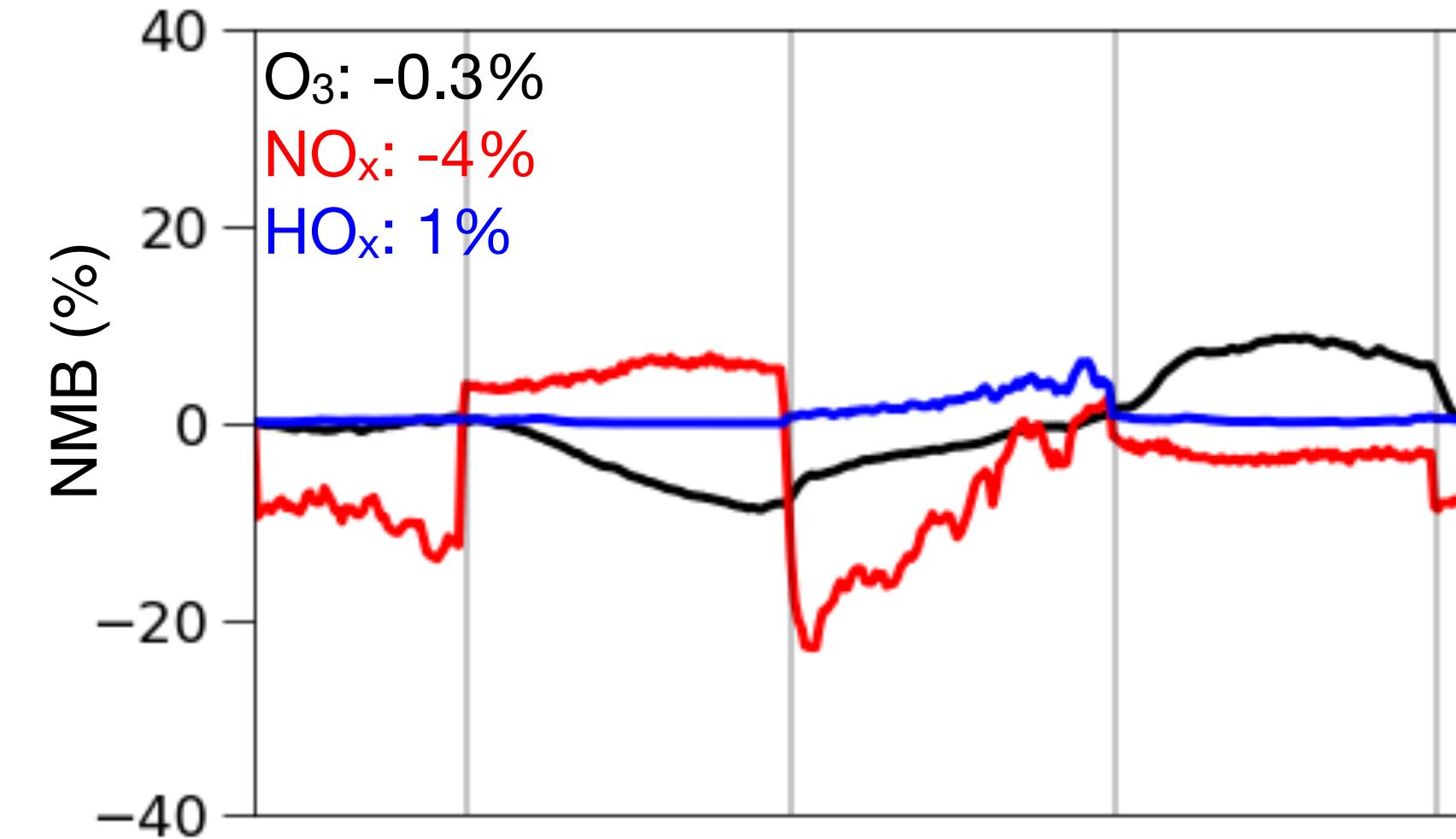
Train:  
JJA 2016

Test:  
July 2017

# ML solvers have different seasonal fits of accuracy

Separate ML solvers for:

- Species
- Season

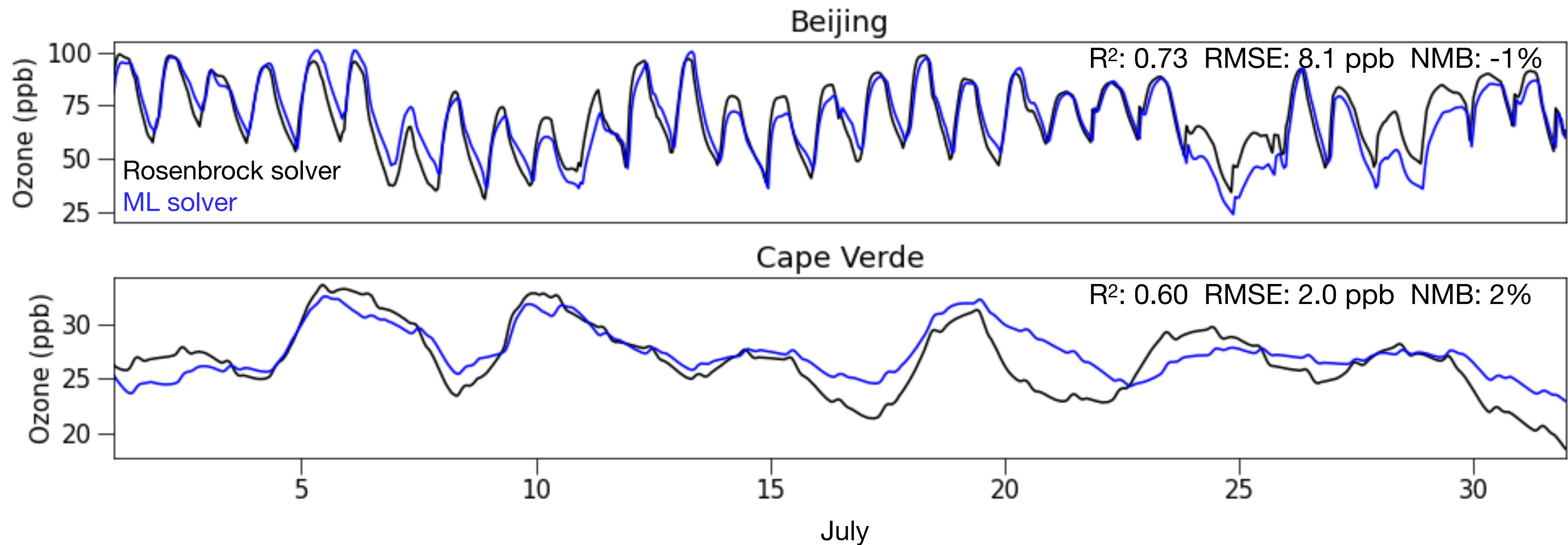


Month

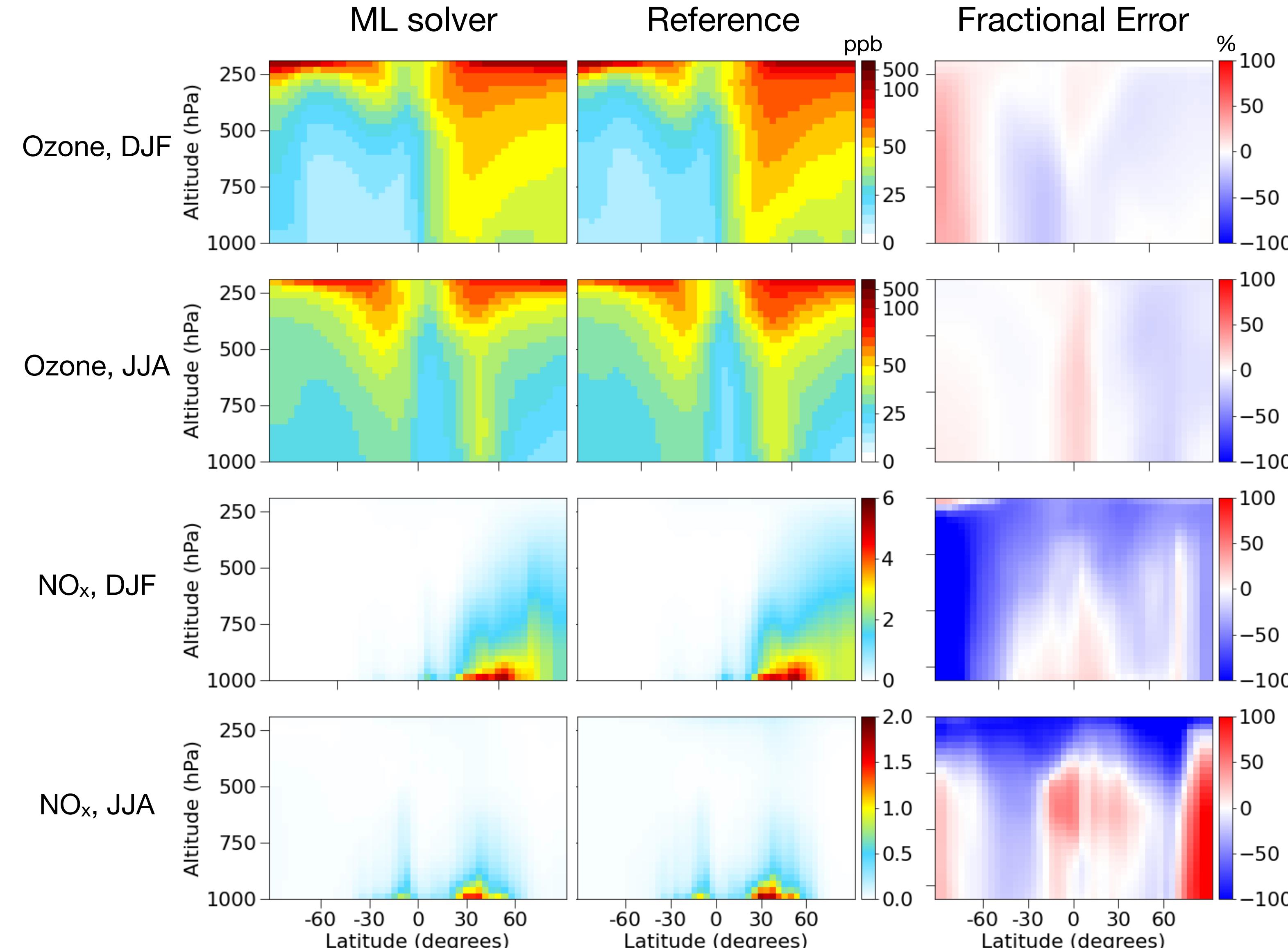
Month

Kelp et al., in review

# ML solver able to capture the diurnal and synoptic variability of ozone at polluted and clean sites



# Errors are largest at remote latitudes and high altitudes due to chemical error accumulation as air ages



# Takeaways

- Application of ML chemical solver in global 3-D atmospheric chemistry models **may require online training**.
- Stable** year-long global simulation of chemistry **can be achieved** with a ML solver applied to the Super-Fast mechanism in GEOS-Chem.
- Computational speedup is **five-fold** relative to the reference Rosenbrock solver in GEOS-Chem.
- Large regional biases for ozone and NO<sub>x</sub> under remote conditions where **chemical aging leads to error accumulation**.
  - Regional biases remain a **major limitation** for practical application, and ML emulation would be more difficult in a more complex mechanism.



**Makoto Kelp**

