# Source and Sink Attributions From Satellites Using Deep Learning Models


Kang Sun

Associate Professor, Department of Civil, Structural and Environmental Engineering

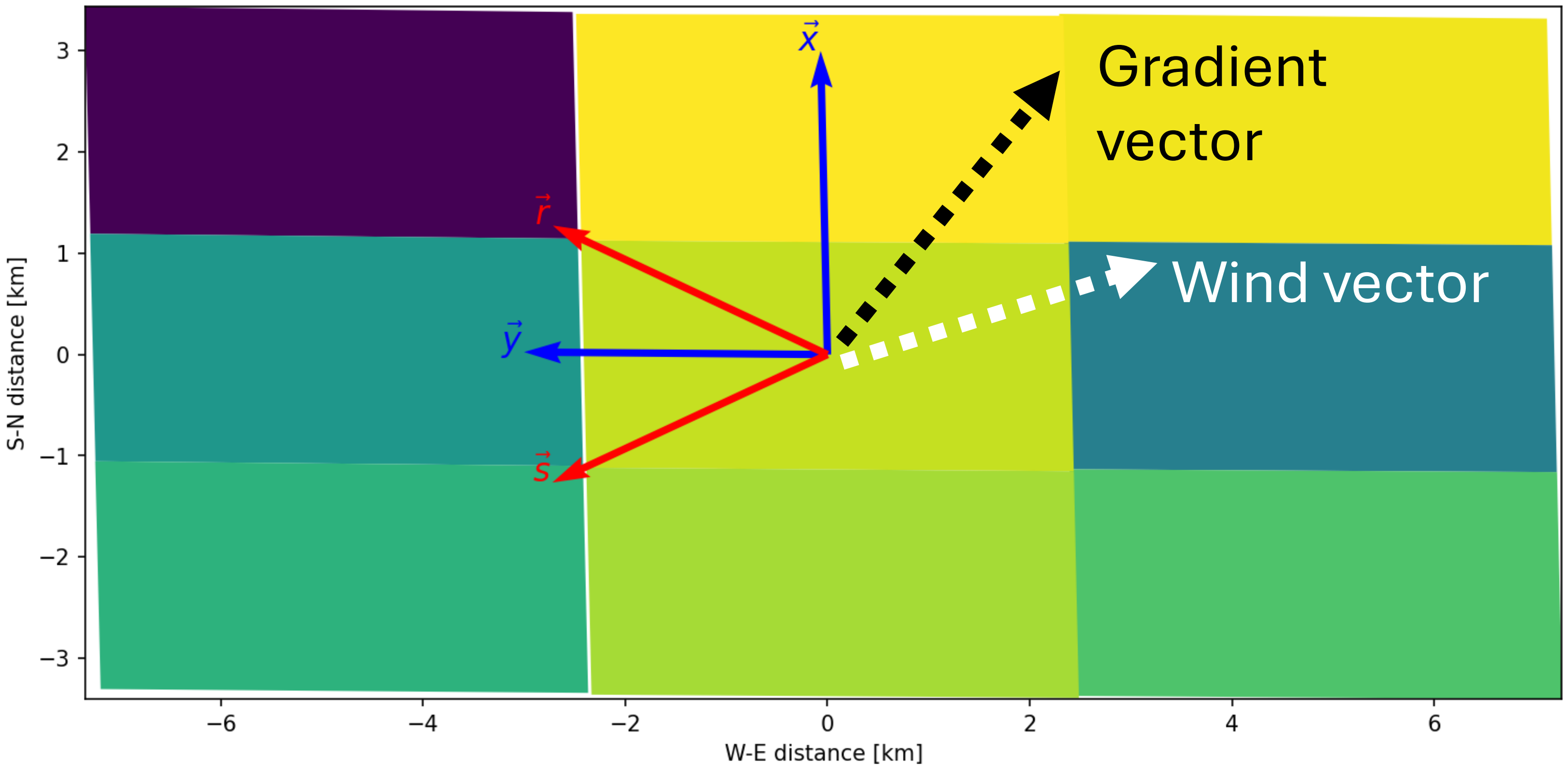
University at Buffalo


6/18/2026

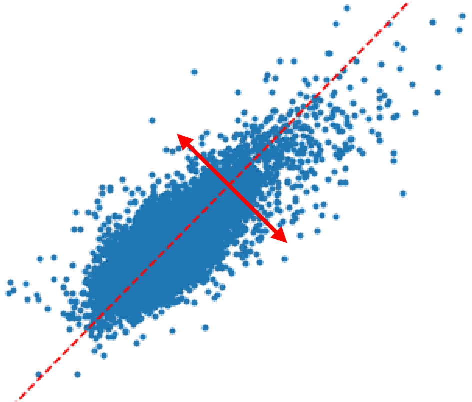
# Directional derivative (DD) of satellite columns (Ω) reflects flux

- "xy" realization: $\vec{u} \cdot (\nabla\Omega) = u_x \frac{\partial\Omega}{\partial x} + u_y \frac{\partial\Omega}{\partial y}$

DD = gradient dot wind

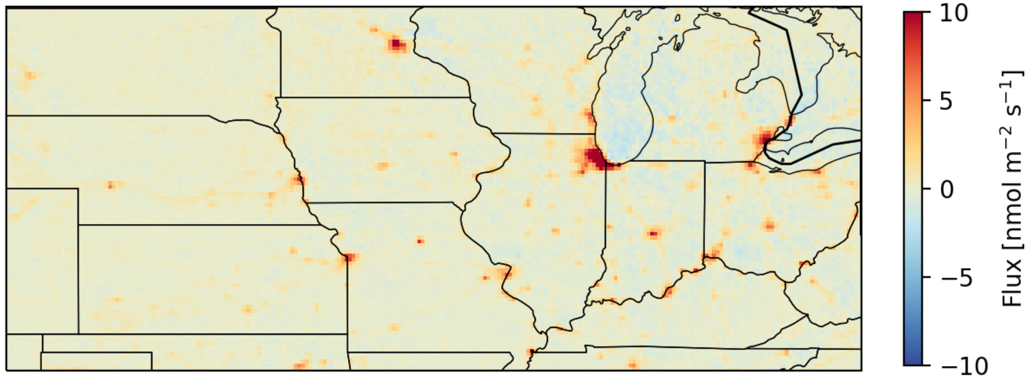


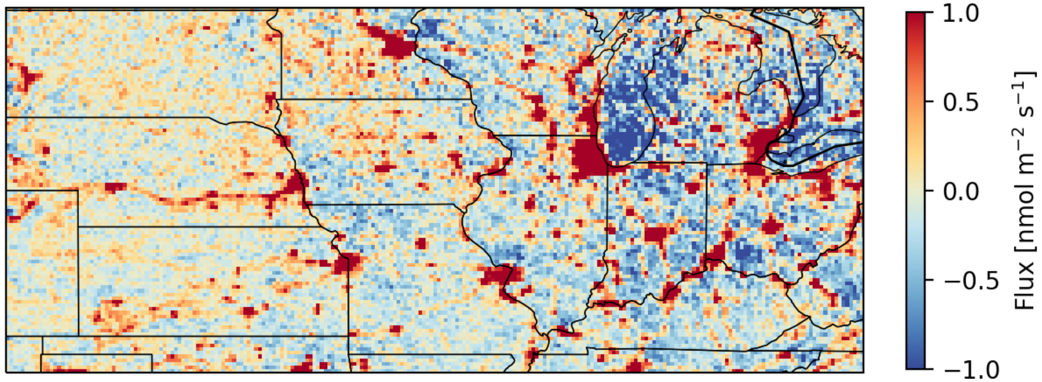

- "rs" realization: $\vec{u} \cdot (\nabla\Omega) = u_r \frac{\partial\Omega}{\partial r} + u_s \frac{\partial\Omega}{\partial s}$
- xy and rs are random (noisy) realizations of the same signal:

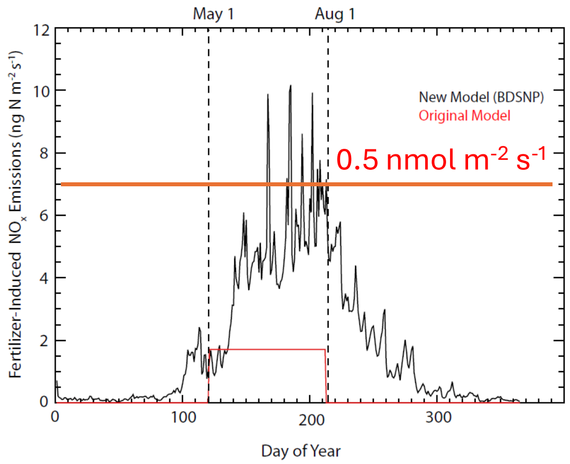


# Where is soil NOx on a multiyear DD (net flux) map?

- Midwest corn receives intensive nitrogen fertilization, yet soil NOx does not show up as the second largest source
- Signal vs. noise vs. interference:
  - Aggregated monthly, the noise floor is ~1-2 nmol $m^{-2}$ $s^{-1}$
  - Peak fertilizer-induced NOx < half of noise
  - Over a satellite-resolvable grid (~10 km), corn accounts for 20%-40% at heart of corn belt
    - Diluted most by soybeans (little N fertilization) -> signal ~ 10% of noise at 1M
  - Fossil fuel interferences at 10s nmol $m^{-2}$ $s^{-1}$
  - Chemical loss at –(0.5-1) nmol $m^{-2}$ $s^{-1}$
    - Soil NOx signal typically "under the water"




Hudman et al. 2012, ACP

# Theory relating DD to sources and sink

- $E = \vec{u} \cdot (\nabla \Omega) + k\Omega + X\Omega\overrightarrow{u_0} \cdot (\nabla z_0)$; $k$: reactivity; $X$: inverse scale height

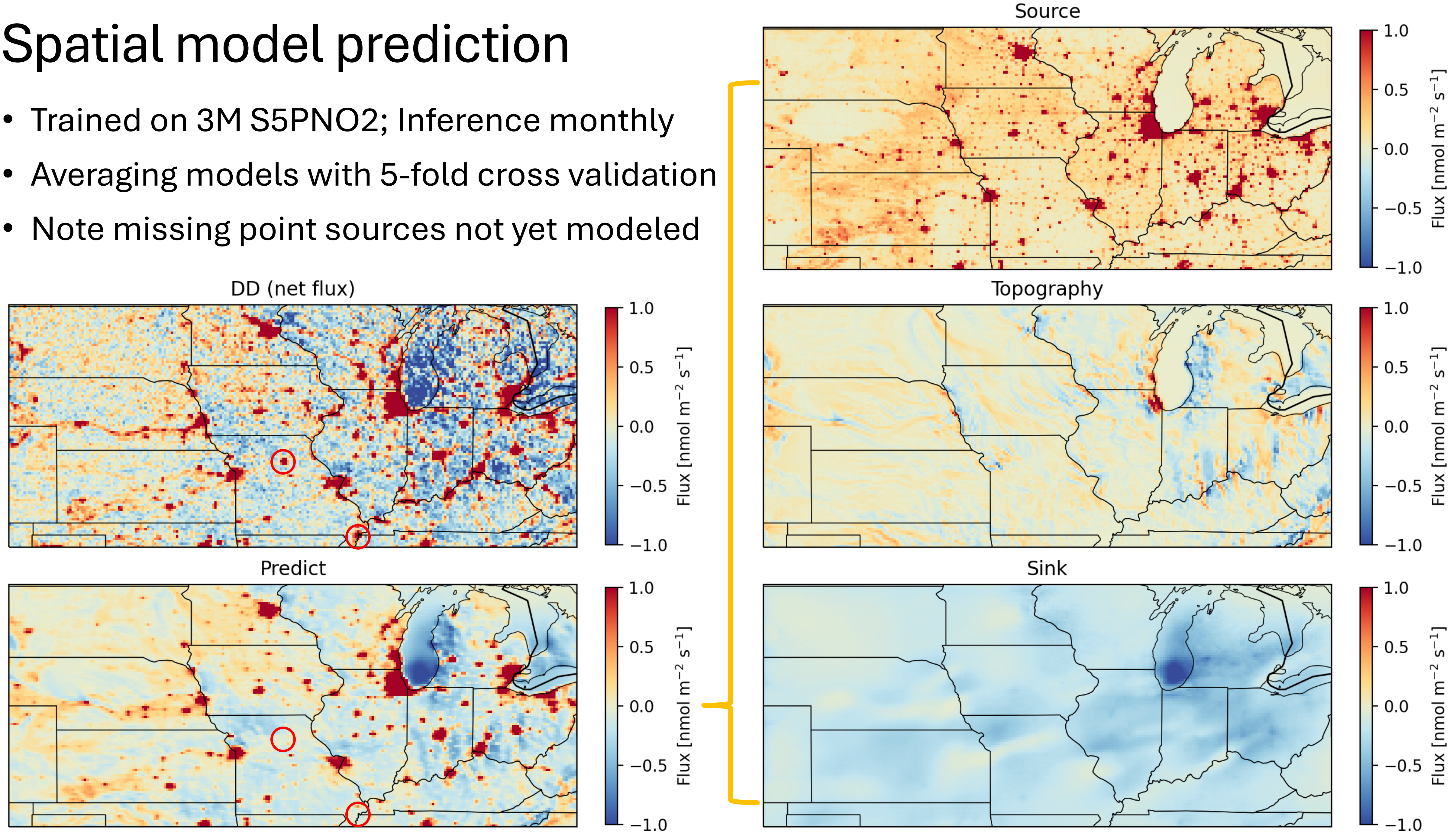
  Source | DD of Ω | Sink | Topography

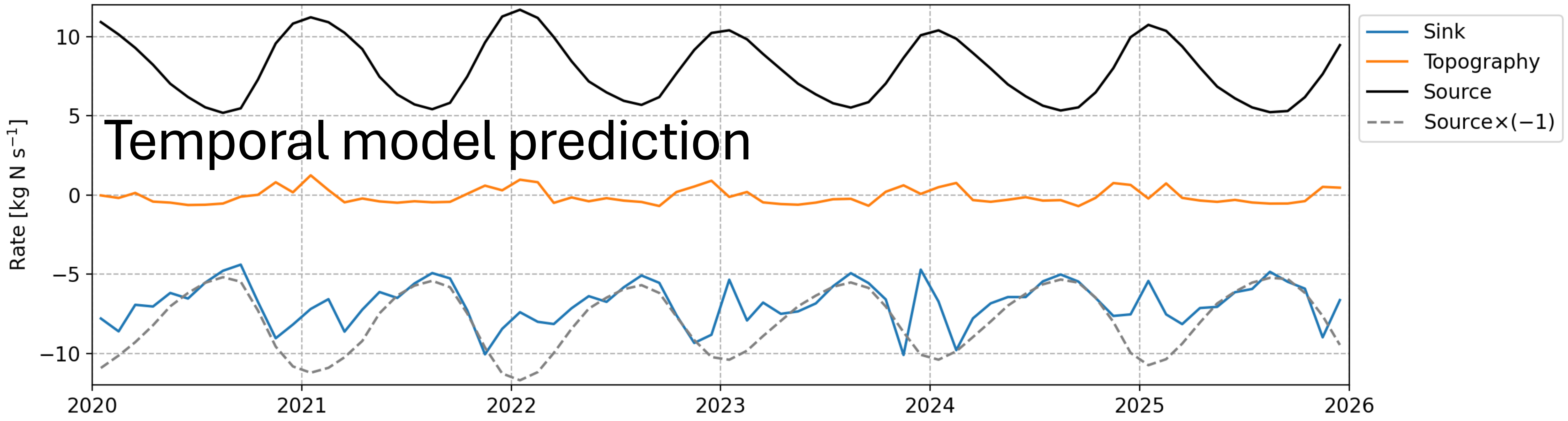
- Decomposing emissions sources as $E = \sum E_i F_i$
  - Example: two same-acreage land types ($F_1 = F_2 = 50\%$) with emissions $E_1 = 9.5$ nmol $m^{-2}$ $s^{-1}$ and $E_2 = 0.5$ nmol $m^{-2}$ $s^{-1}$ give $E = 5$ nmol $m^{-2}$ $s^{-1}$
- Rearrange:
  - $\vec{u} \cdot (\nabla \Omega) = k(-\Omega) + X\left(-\Omega\overrightarrow{u_0} \cdot (\nabla z_0)\right) + E_1 F_1 + E_2 F_2 + \cdots$
- Like a linear regression model (target = sum(coefficient x predictor)), but
  - Coefficients are functions of space and time (lat, lon, linear trend, seasonality)
  - Coefficients *must be non-negative*
  - Coefficients should be spatially smooth, and not significantly correlated
  - Coefficients learned as a feature-wise-modulated U-Net (~9e6 parameters)
- Wrapped by a learnable super-Gaussian point-spread function

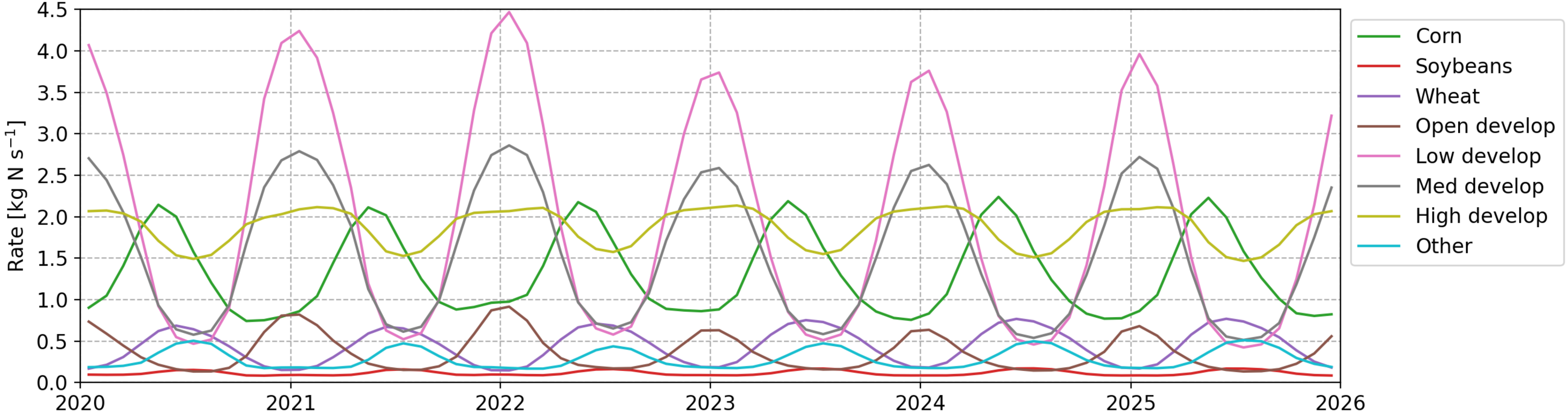
Source: Sun GRL'22; Lonsdale and Sun ACP'23; Ayazpour, Sun, et al. JGR-A'25; Sun et al. JGR-A'25

# Spatial model prediction

- Trained on 3M S5PNO2; Inference monthly
- Averaging models with 5-fold cross validation
- Note missing point sources not yet modeled




Temporal model prediction
Rate [kg N s$^{-1}$]
10
5
0
−5
−10
2020
2021
2022
2023
2024
2025
2026
Sink
Topography
Source
Source×(−1)


Rate [kg N s$^{-1}$]
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
2020
2021
2022
2023
2024
2025
2026
Corn
Soybeans
Wheat
Open develop
Low develop
Med develop
High develop
Other

# Concluding remarks

- TEMPO?
  - Adding diurnal cycle to temporal feature, to 5 elements: linear time, sin/cos of fractional year, and plus *sin/cos of fractional day*
  - Fitting point-spread functions conditioning on specific instruments
  - Transfer/continual learning from TROPOMI-pretrained model
  - Previous/future instruments?