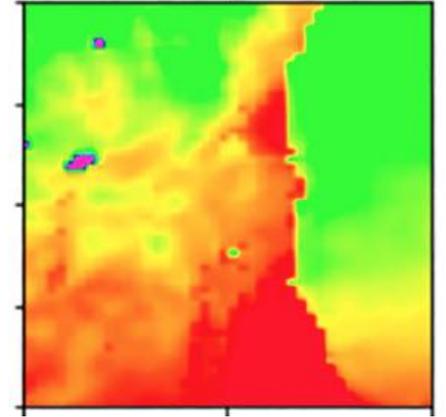


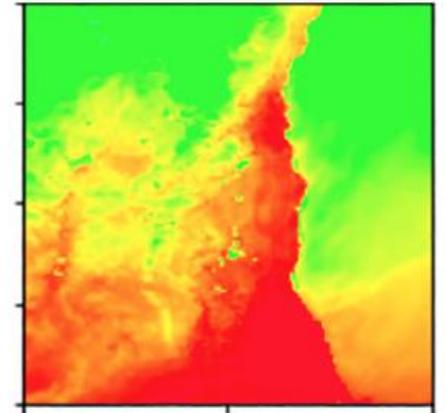
Efficient Super-Resolution of Near-Surface Climate Modeling Using the Fourier Neural Operator



T_2 (4km)



T_2 (1km)



Peishi Jiang, Zhao Yang, Jiali Wang, Chenfu Huang,
Pengfei Xue, TC Chakraborty, Xingyuan Chen, Yun Qian

RemPlex 2023, PNNL

2023. 11. 14.

Atmospheric downscaling to $\geq 1\text{km}$ is critical to a variety of land surface studies

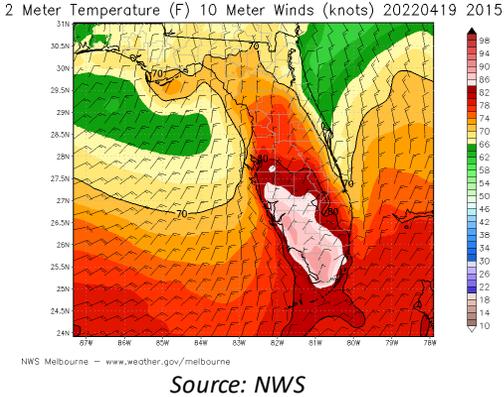
Need



Challenge

- High-reso simulation (e.g., 1km) at meso-scale
- facilitate the heat wave studies.
- drive watershed modeling

- Dynamical downscaling using model such as WRF is computationally expensive.
- **Question: how to efficiently generate high-reso simulation?**

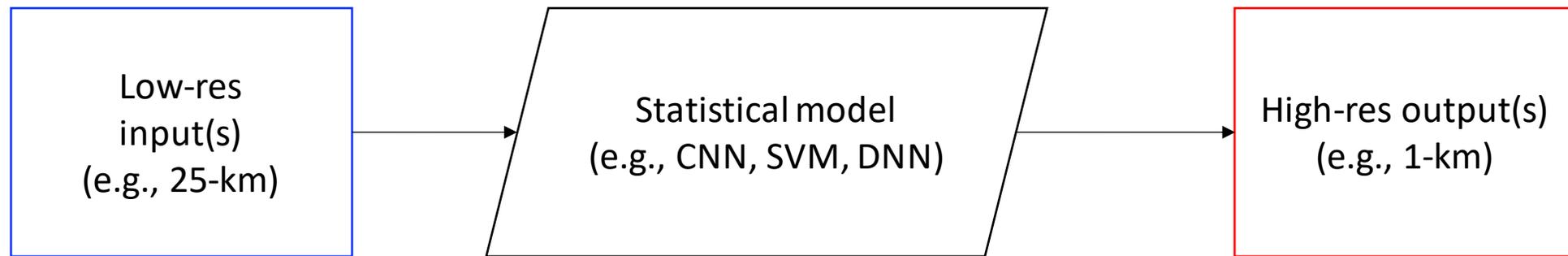


High Resolution



Low Resolution

Gap: traditional statistical downscaling only performs the mapping on **fixed resolutions**.



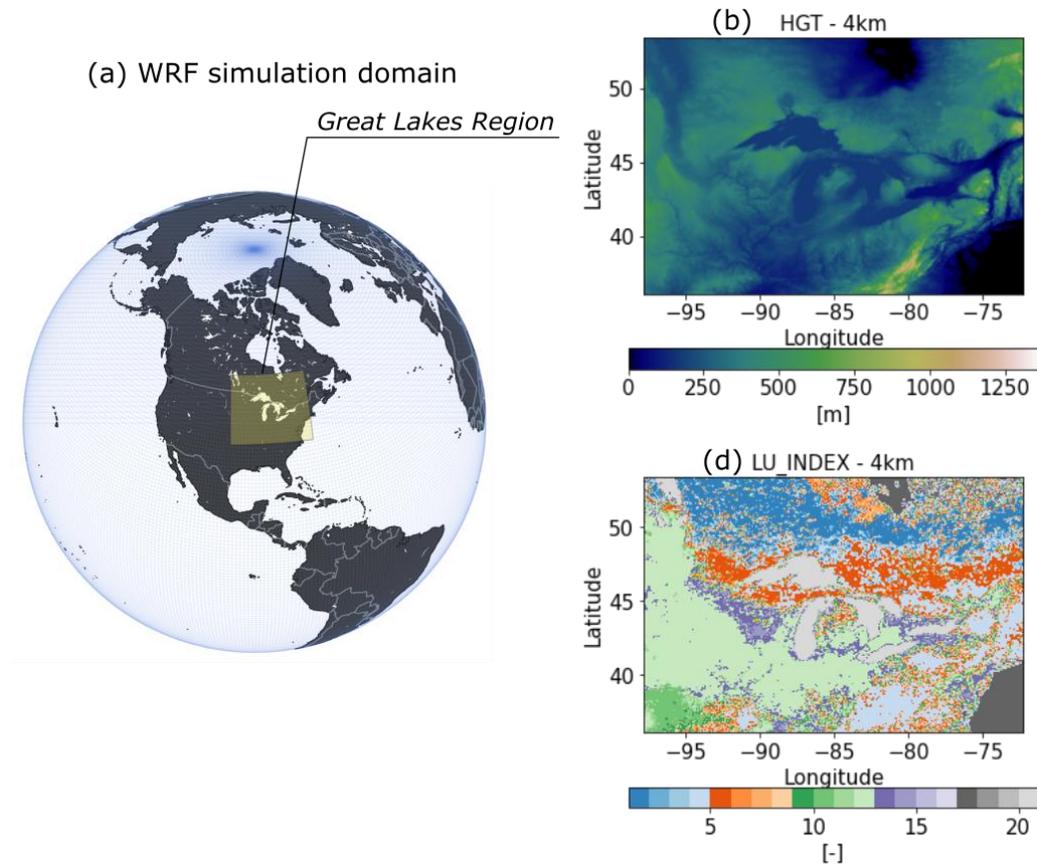
- *Retraining is needed for a different high-res task*
- *High-reso data is needed for training*



The **objective** is to develop efficient super-resolution of near-surface climate modeling.

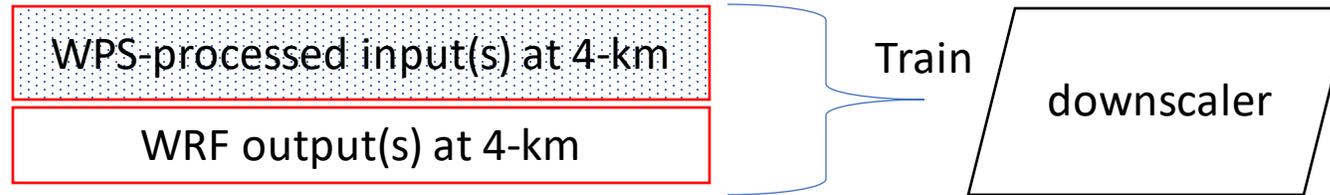
- Study area: Great Lake Region
- Available WRF simulation
 - spatial resolution: 4km
 - temporal resolution: 3hr
 - 2018.6~2018.8

- *Running WRF at 1km scale is extremely computationally expensive!*

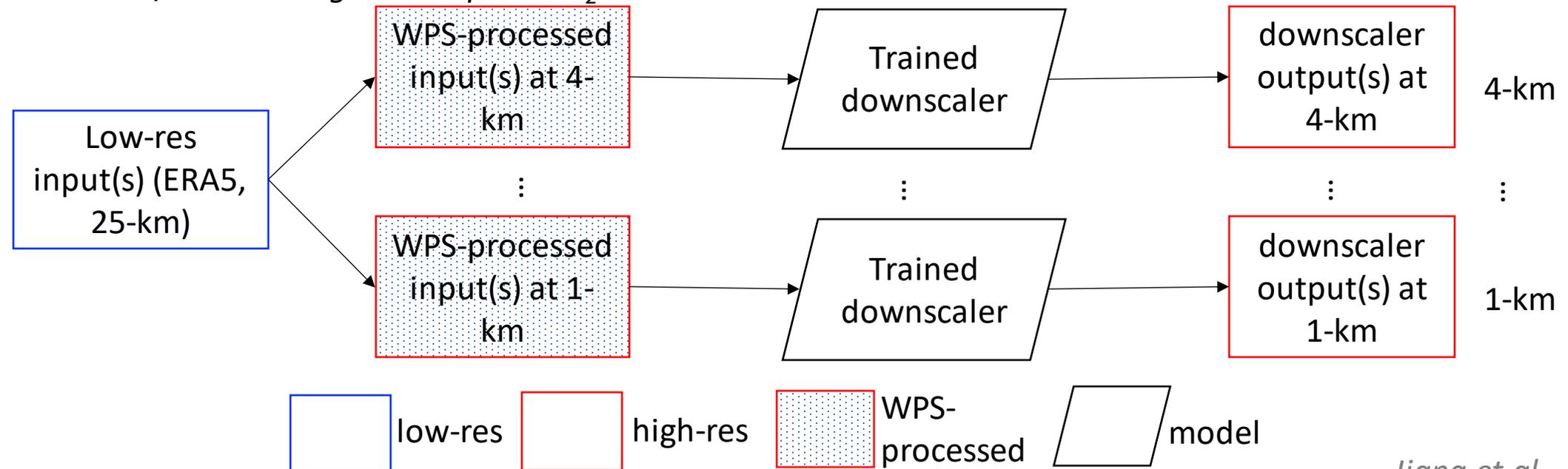


We proposed **zero-shot super-resolution** that allows downscaling at any resolution.

Downscaler trained on a given-res (e.g., 4-km) WRF at time period T_1



Emulation/downscaling at time period T_2



We employed Fourier Neural Operator (FNO) to both **downscale** and **emulate** WRF simulation.

Inputs

- 1000hPa
- 925hPa
- 850hPa

Atmospheric vertical profile

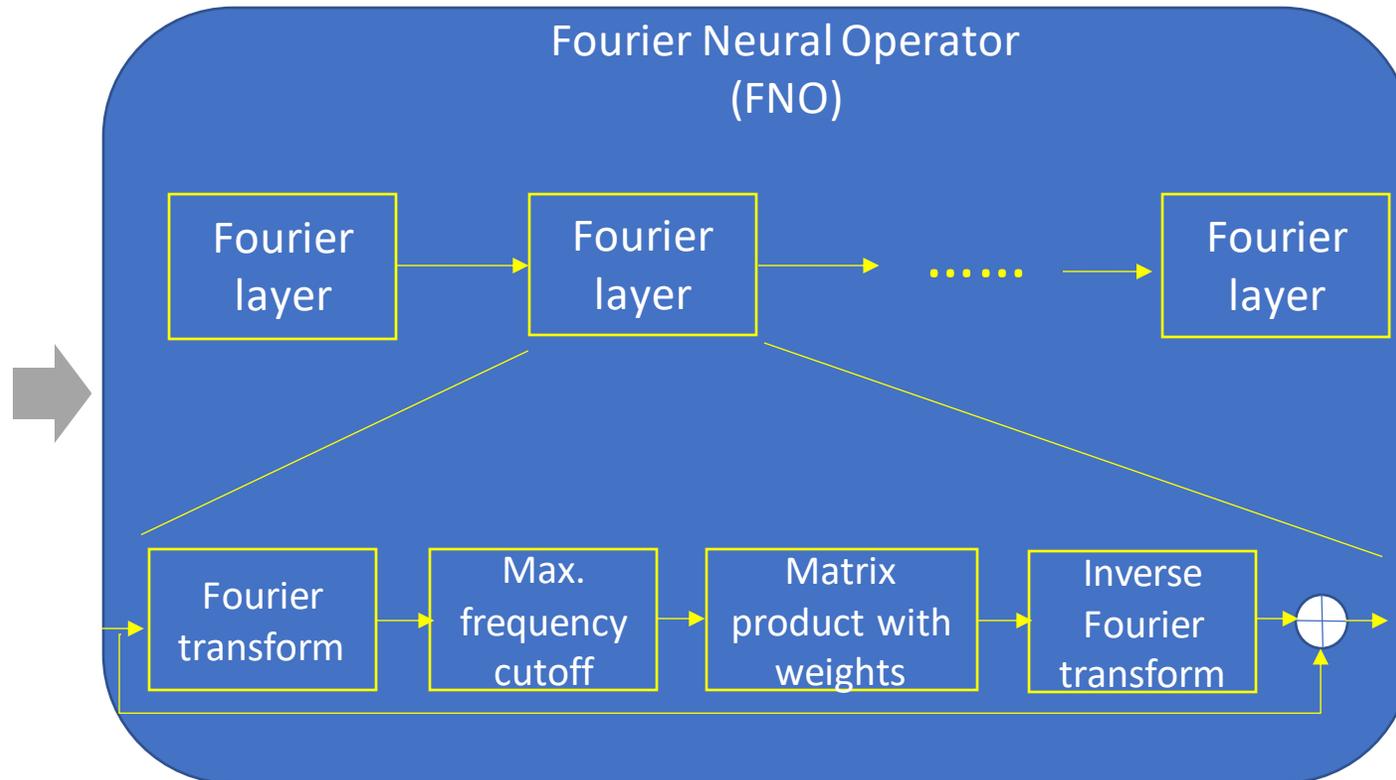
- ✓ UU ✓ RH
- ✓ VV ✓ PRES
- ✓ TT ✓ GHT

Land surface states

- ✓ GLST-SKINTEMP
- ✓ SM-O

Topography

- ✓ HGT_M
- ✓ LU_INDEX



Outputs

Surface heat dynamics

- ✓ T2
- ✓ RH2
- ✓ SH
- ✓ PSFC

- FNO is resolution-invariant (Li et al., 2020)

- FNO can be used as both an emulator and downscaling tool *Jiang et al., JAMES, 2023*

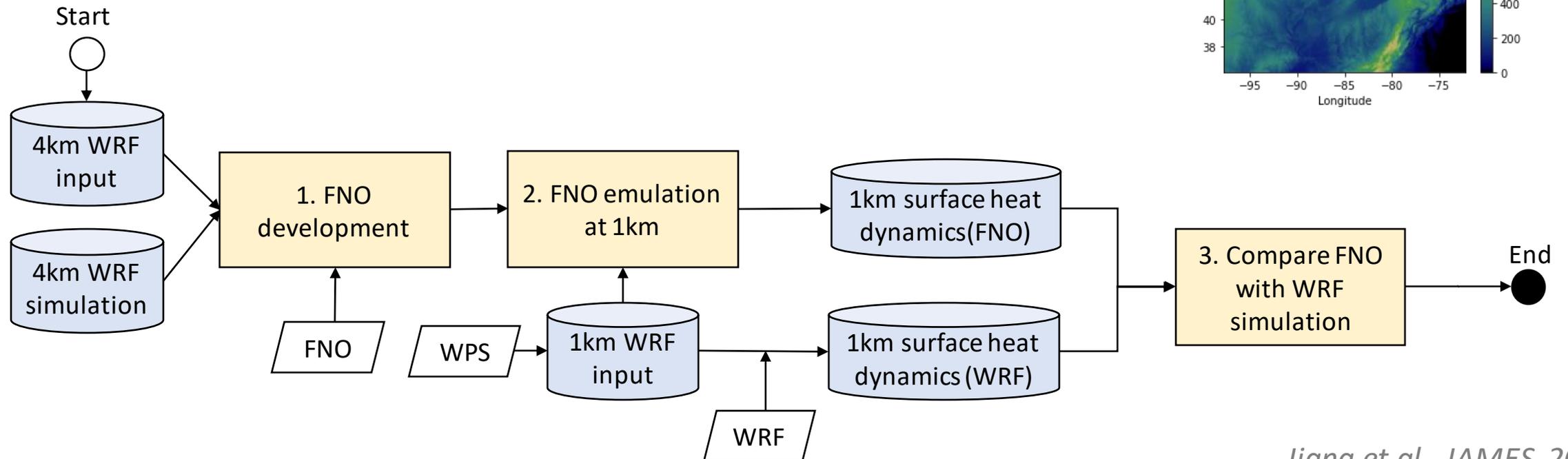
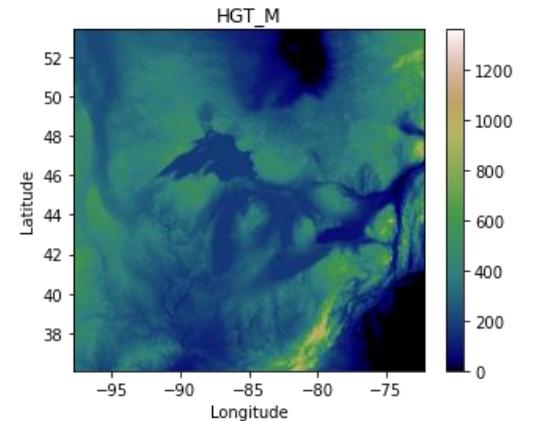
We employed Fourier Neural Operator (FNO) to both **downscale** and **emulate** WRF simulation.

Step 1: FNO emulator development using WRF simulation at 4km

Step 2: FNO emulation at 1km

Step 3: Compare FNO emulation with WRF simulation at 1km

Great lakes Region



We trained the FNO using a **physics-constrained loss** based on the Clausius–Clapeyron equation.

Loss function: $\mathcal{L} = \mathcal{L}_{MSE} + \alpha \mathcal{L}_{CC}$

Mean squared error:

$$\mathcal{L}_{MSE} = \frac{1}{N_x N_t} \sum_t \sum_x [O_t(x) - O_t^{WRFF}(x)]^2$$

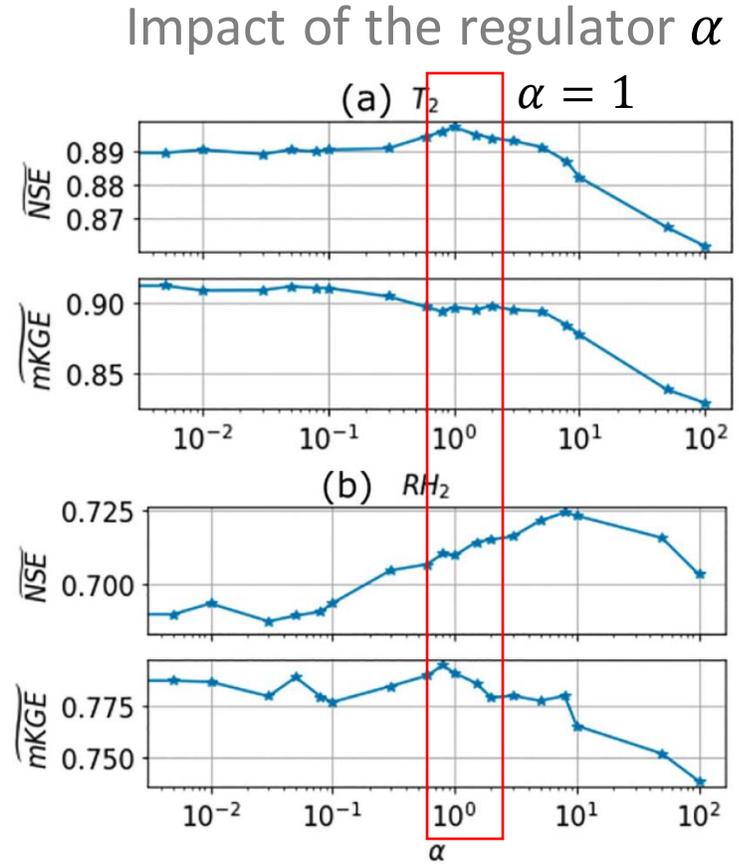
Physics-based loss

$$\mathcal{L}_{CC} = \frac{1}{N_x N_t} \sum_t \sum_x [RH_{2,cc,t}(x) - RH_{2,t}(x)]^2$$

Clausius-Clapeyron relation

$$w = \frac{SH}{1 - SH} \quad e = \frac{w}{w + 0.622} \times PSFC,$$

$$e_{sat} = 610.78 \times \exp\left(\frac{17.27 \times T_2}{237.3 + T_2}\right) \quad RH_2 = \frac{e}{e_{sat}} \times 100.$$



mKGE: the modified Kling–Gupta Efficiency
NSE: the Nash–Sutcliffe model Efficiency

FNO emulation performance at 4km resolution

Performance on the pressure field (PSFC) is the best.

Followed by T_2 , RH_2 , and SH.

FNO performs worse in lake/water regions.

mKGE: the modified Kling–Gupta Efficiency
NSE: the Nash–Sutcliffe model Efficiency

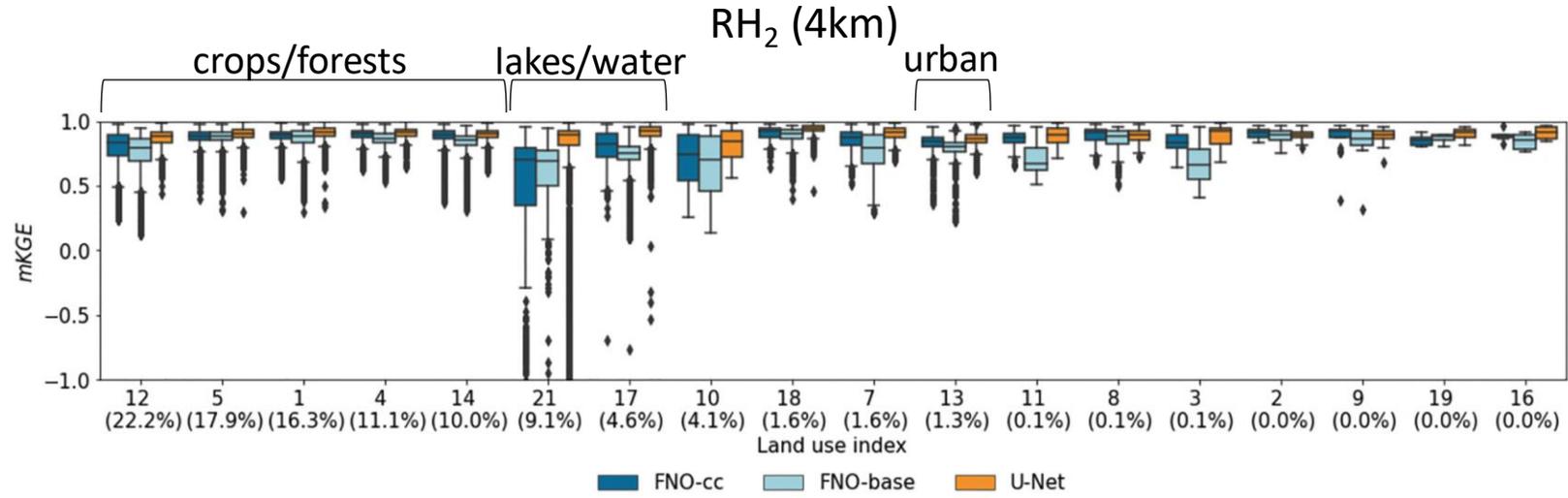
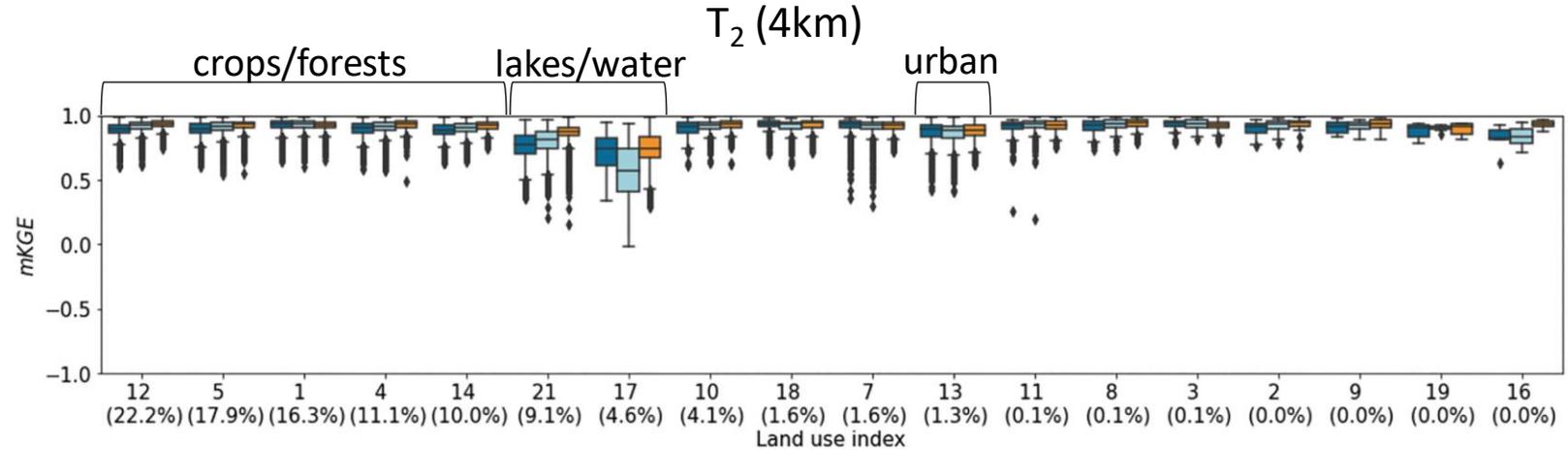
The impact of land use on FNO performance

FNO performs well in most land use, particularly the dominant vegetated regions.

FNO performs worse on lakes/water region.

FNO performs a lightly worse on the urban region.

In short, FNO struggles to learn dynamics from less represented clusters of data.

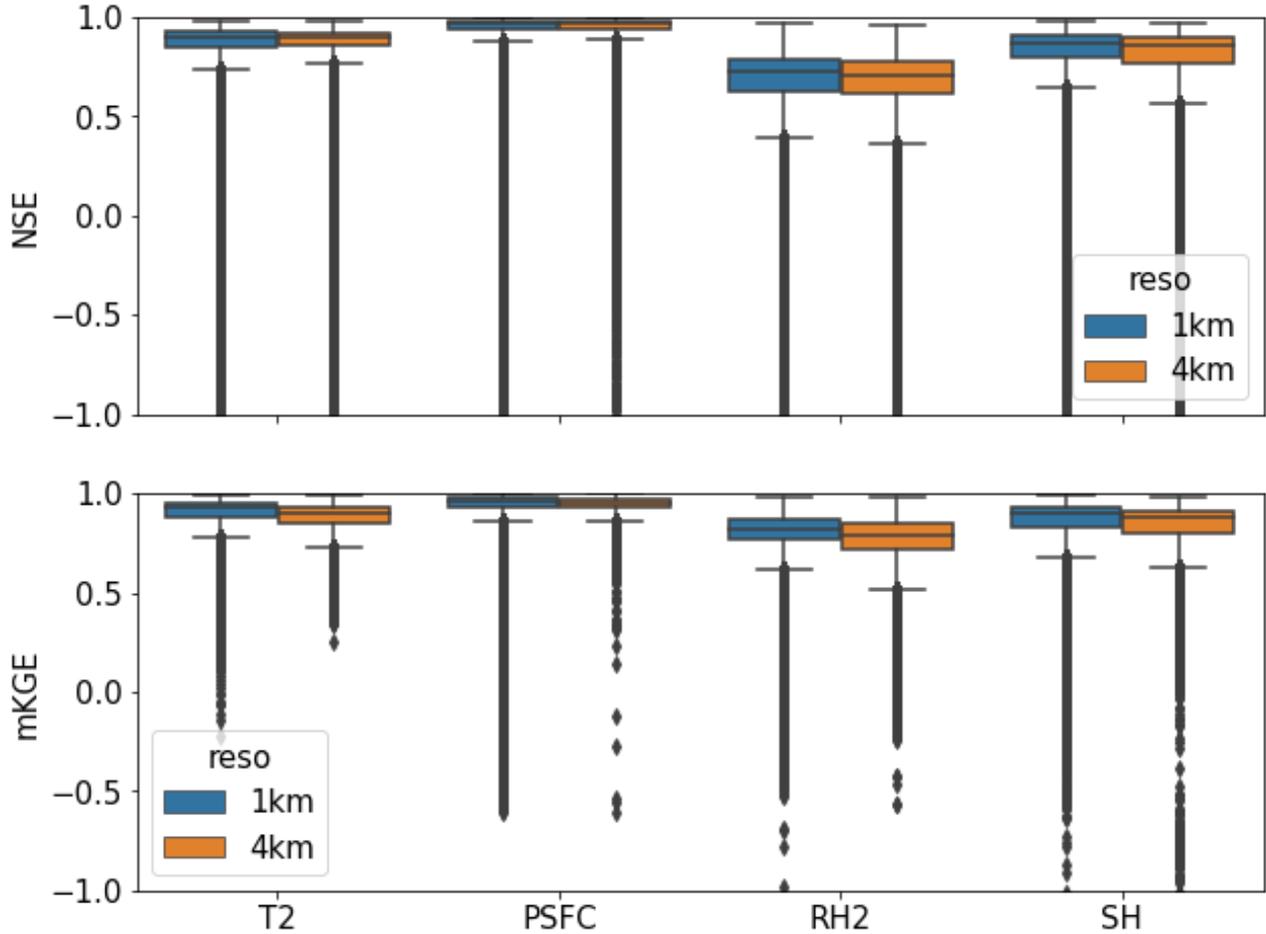


FNO-cc (dark blue), FNO-base (light blue), U-Net (orange)

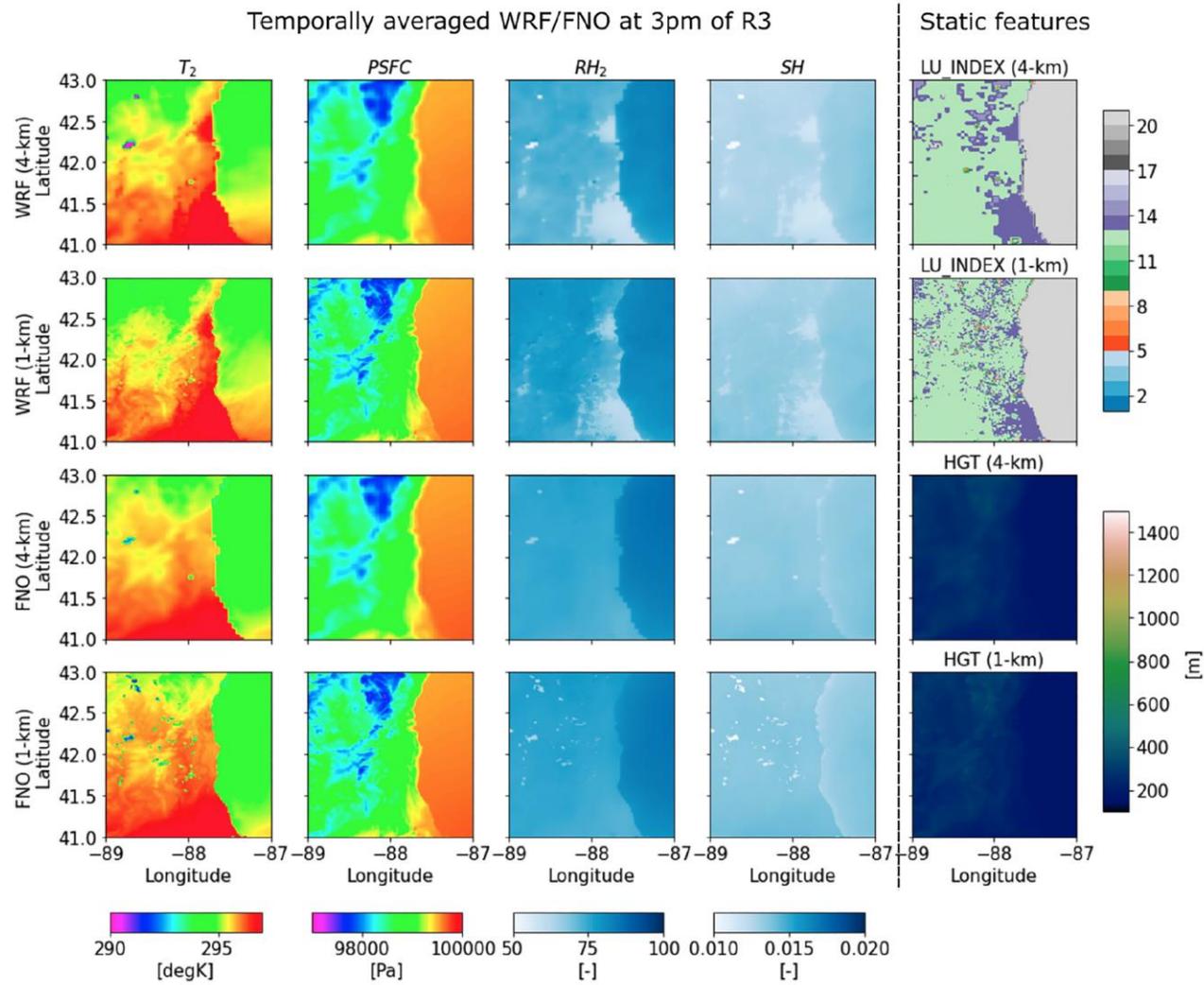
FNO downscaling performance at 1km resolution.

With slight variation, the performance are almost consistent between 1km and 4km.

FNO downscaling is able to keep the performance!

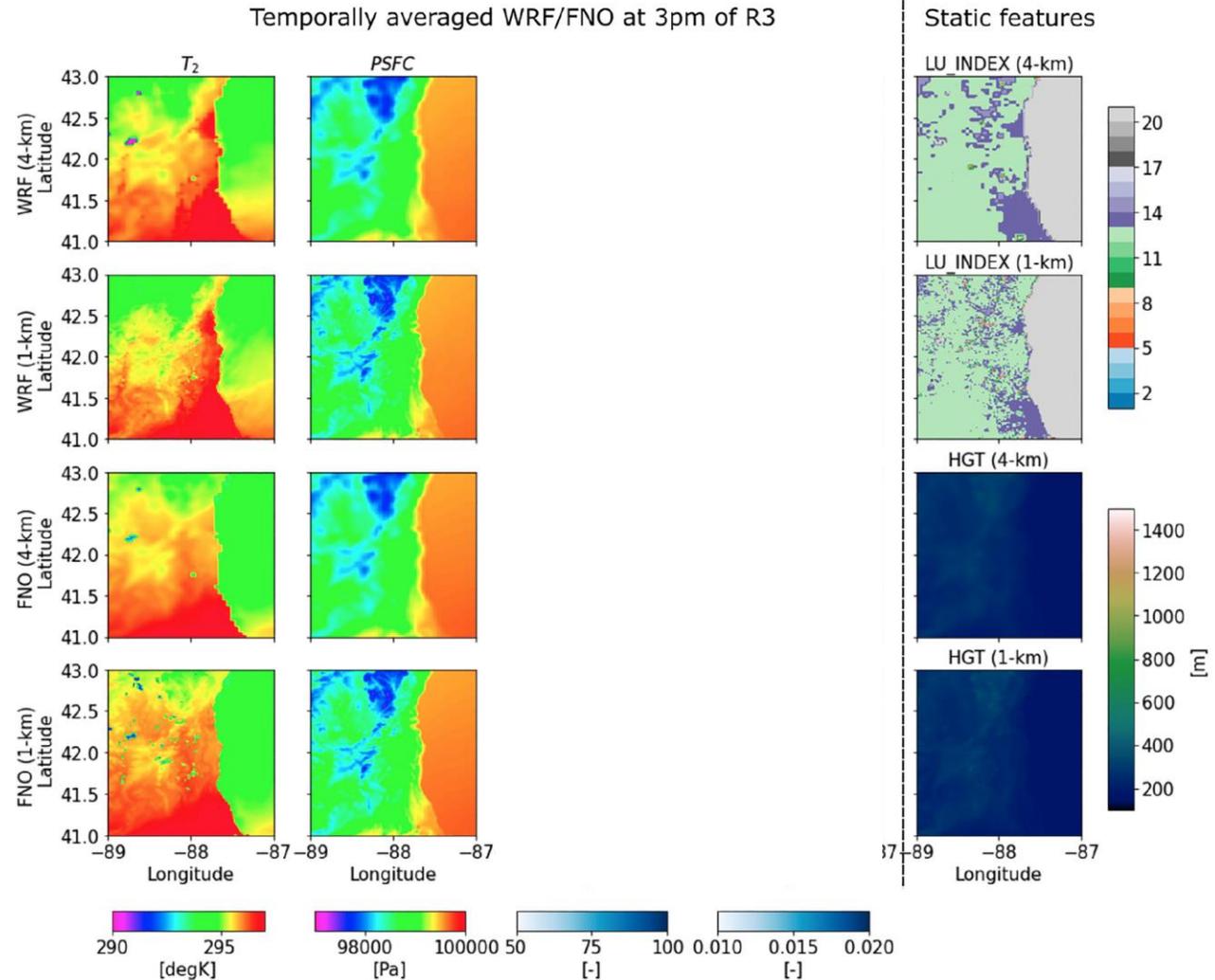


A zoom-in snapshot in Chicago area.



A zoom-in snapshot in Chicago area.

FNO 1km emulation of T2 and PSFC is quite consistent with WRF.

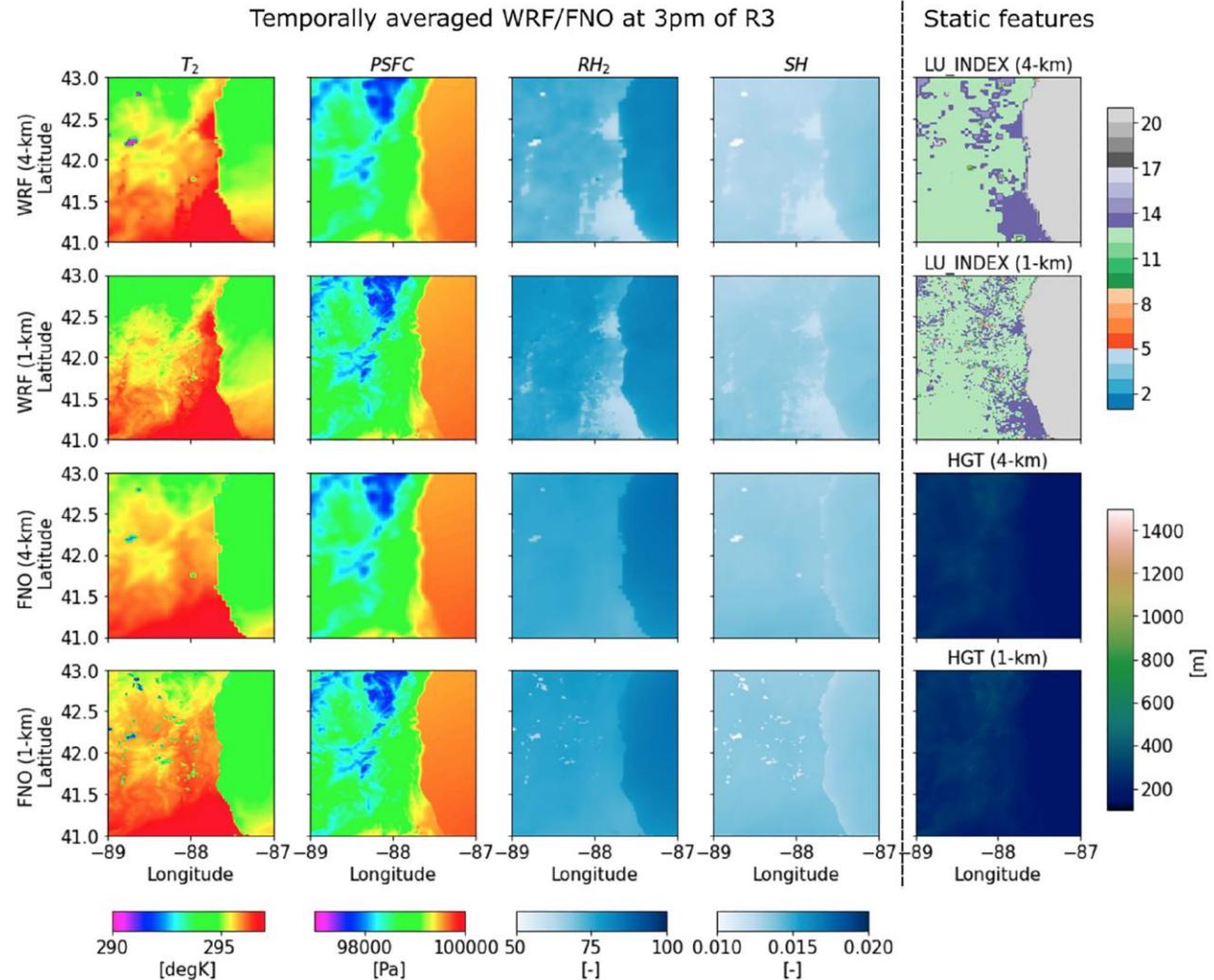


A zoom-in snapshot in Chicago area.

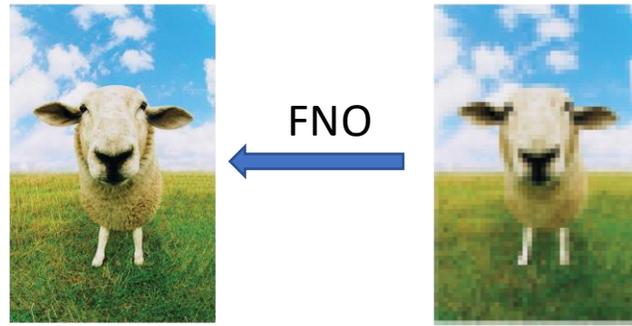
FNO 1km emulation of T2 and PSFC is quite consistent with WRF.

However, FNO is unable to capture the urban impact on the humidity at both resolutions.

The performance of FNO-1km is generally similar to that of FNO-4km.



Conclusions



Thank you!



We used the Fourier neural operator (FNO) to perform zero-shot super-resolution on near-surface heat-related estimates



Incorporating a physics-constrained loss based on the Clausius–Clapeyron equation improves the emulation performance of the trained FNO.



Trained on a 4-km WRF simulation, the FNO generates a 1-km emulation that captures fine-grained climate features induced by topography.



Despite its downside, zero-shot super-resolution can be an alternative for atmospheric downscaling when computational budget is limited.