#198

A 3D super-resolution of wind fields via physics-informed pixel-wise self-attention generative adversarial network

Takuya Kurihana[1,2], Kyongmin Yeo[2], Daniela Szwarcman[3], Bruce Elmegreen[2], Karthik Mukkavilli[3], Johannes Schmude[2], Levente Klein[2]

1 University of Chicago, Department of Computer science, 2 IBM Research Yorktown Heights
3 IBM Research Brazil, 4 IBM Research Zurich

Email: tkurihana@uchicago.edu

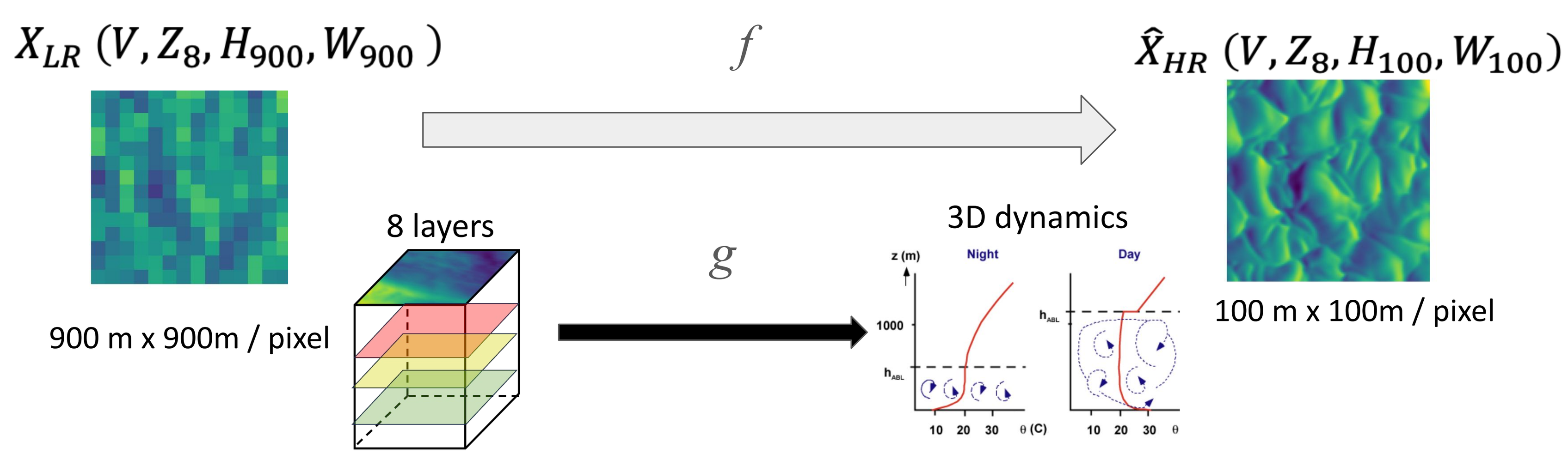
NEURAL INFORMATION PROCESSING SYSTEMS

3D super-resolution of wind fields

Physics-informed **3D Super Resolution (SR)** is needed to **reduce computational complexity in high-resolution weather simulation** to

- Compute advection and diffusion for tracing source of Greenhouse Gasses (GHG) **– a key measurement for policy making to tackle GHG gas emission**
- **Literature in SR to atmospheric data often targeted on 2D**

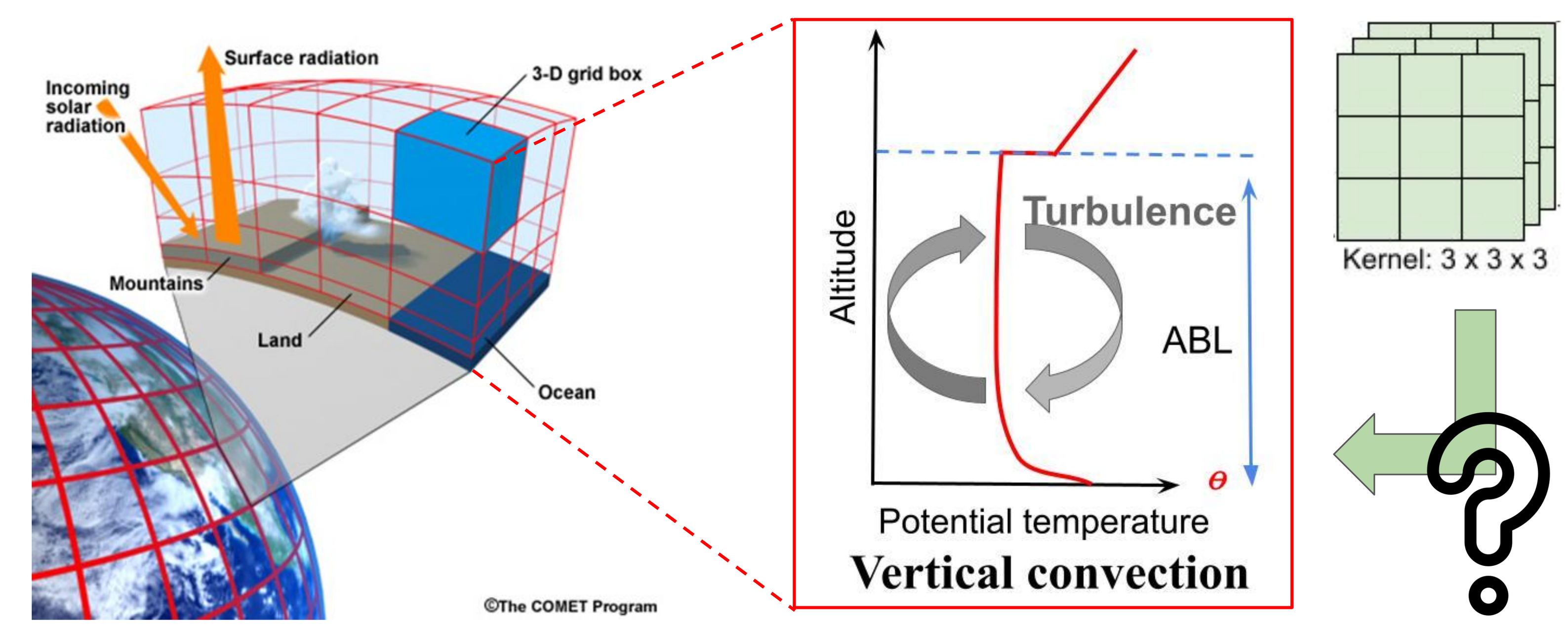
→ We need a **3D SR neural network** f, which learns 3D dynamics via g!



Standard conv filters fall short in capturing physics

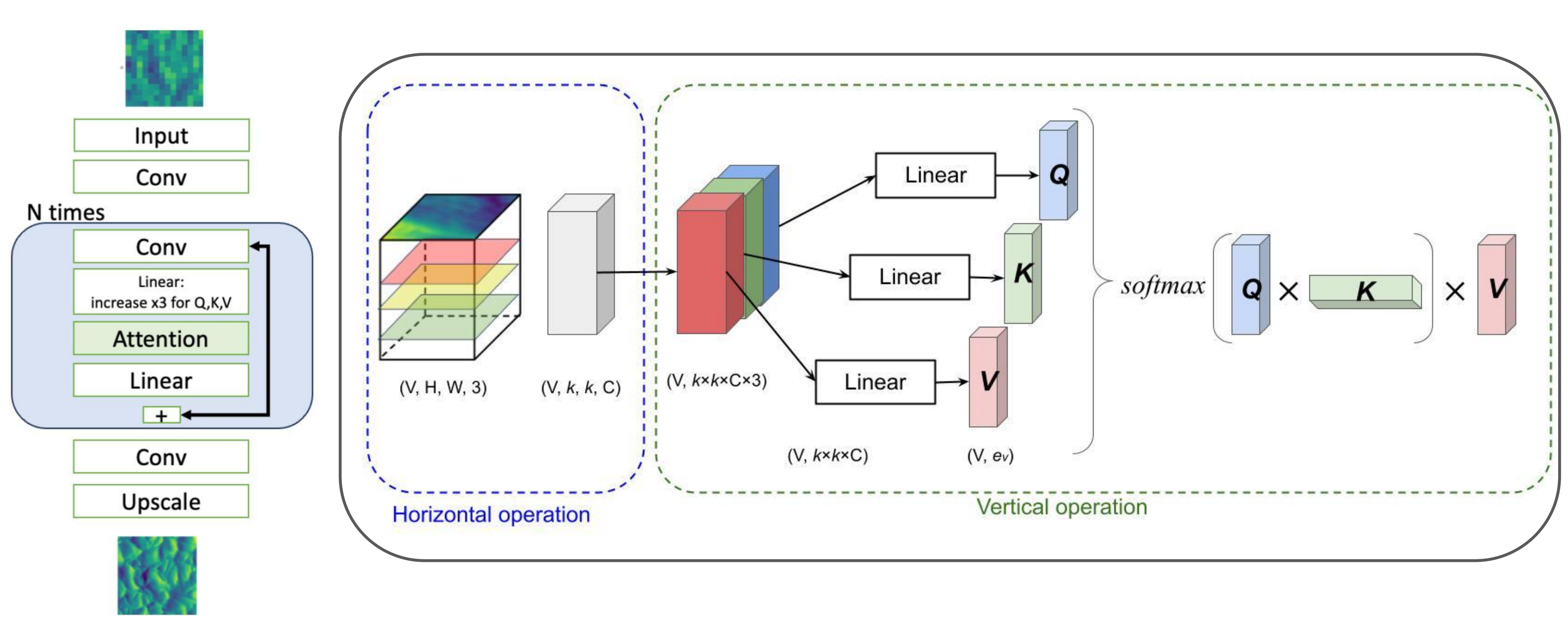
Issue:

- CNN limits learning data at 3 x 3 x 3 fixed areas, but **3D dynamics in weather system varies day and night vertically**
- Numerical weather model is **vertically non-uniform** - 3 x 3 x 3 kernel may **truncate signals in 3D dynamics**

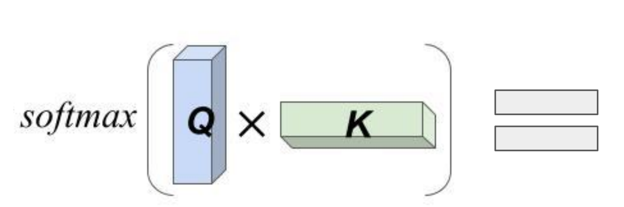


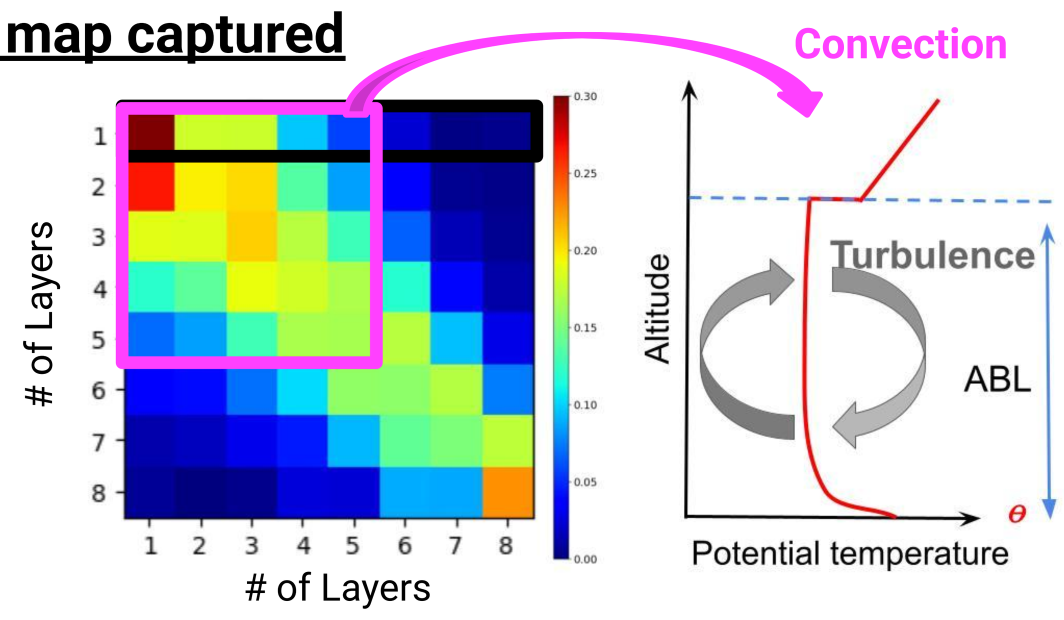
Pixel-Wise self-Attention Network: PWA Network

Pixel-Wise self-Attention Network (PWA) computes (1)horizontal and (2)vertical information separately to better capture 3D weather dynamics



Interpret what self-attention map captured





Each row tells strength of signals bounded by [0,1] between adjacent layers, associating convection in weather systems

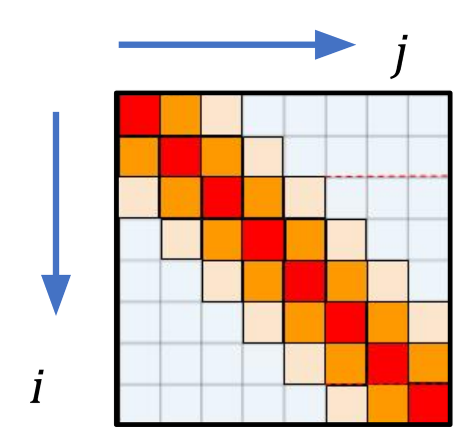
PWA + GAN: How to train model?

Self-attention regularization + Rescaling

To highlight higher signal/weaken lower signal on self-attention map M, we regularize as a loss term $R(M)$:

$$R_i = \sum_{j=1}^{V} M_{ij}^2,$$

$$R(M) = \sum_{i=1}^{V} \frac{1}{R_i},$$

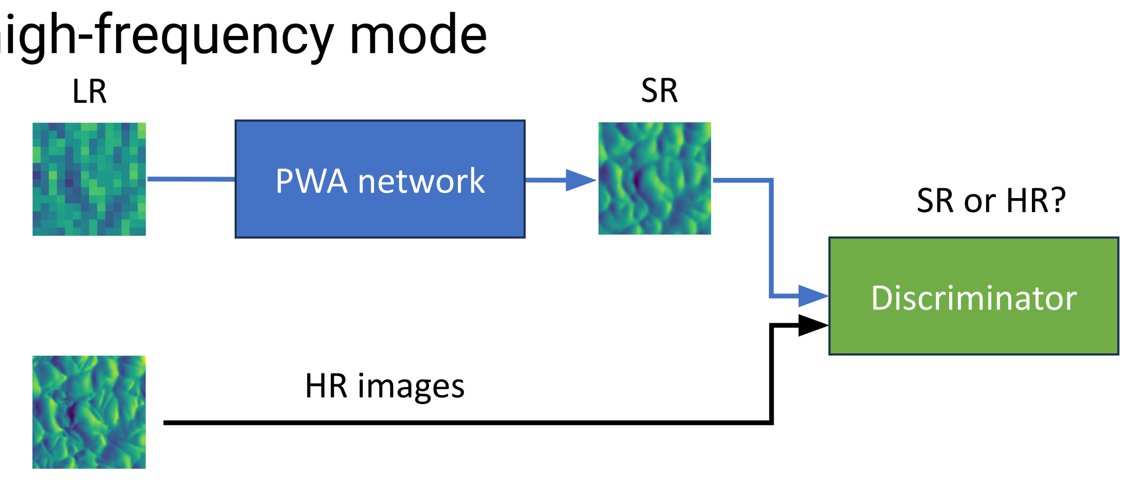


A **trainable scale matrix** $\boldsymbol{\Delta}$ rescales M to have values larger or smaller than the range [0,1], adding further highlighting in learning dynamics:

$$M^{\text{rescale}} = \Delta \cdot M$$

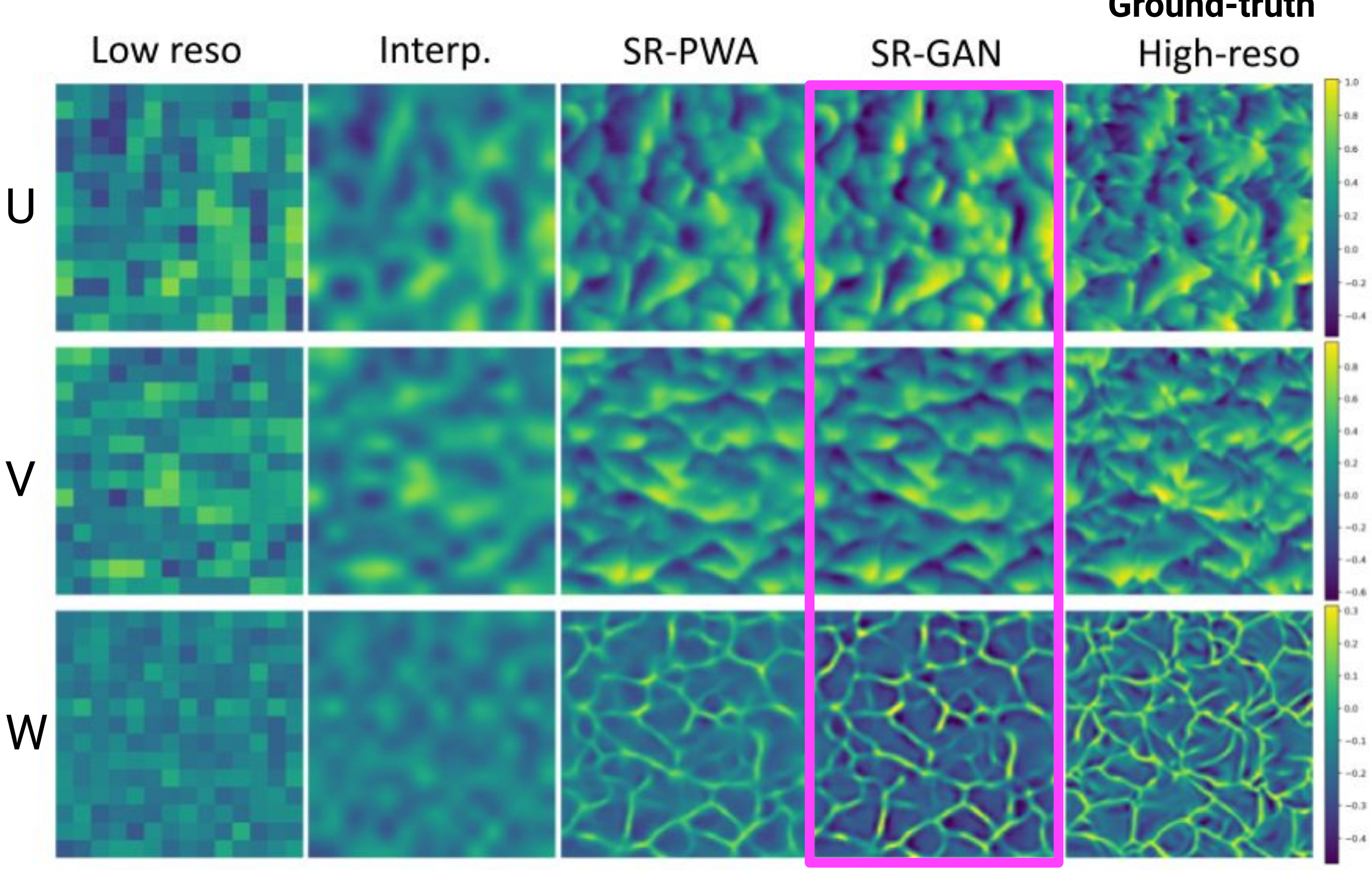
Generative Adversarial Network (GAN)

Add adversarial loss to a generator (PWA network) to include signals at high-frequency mode

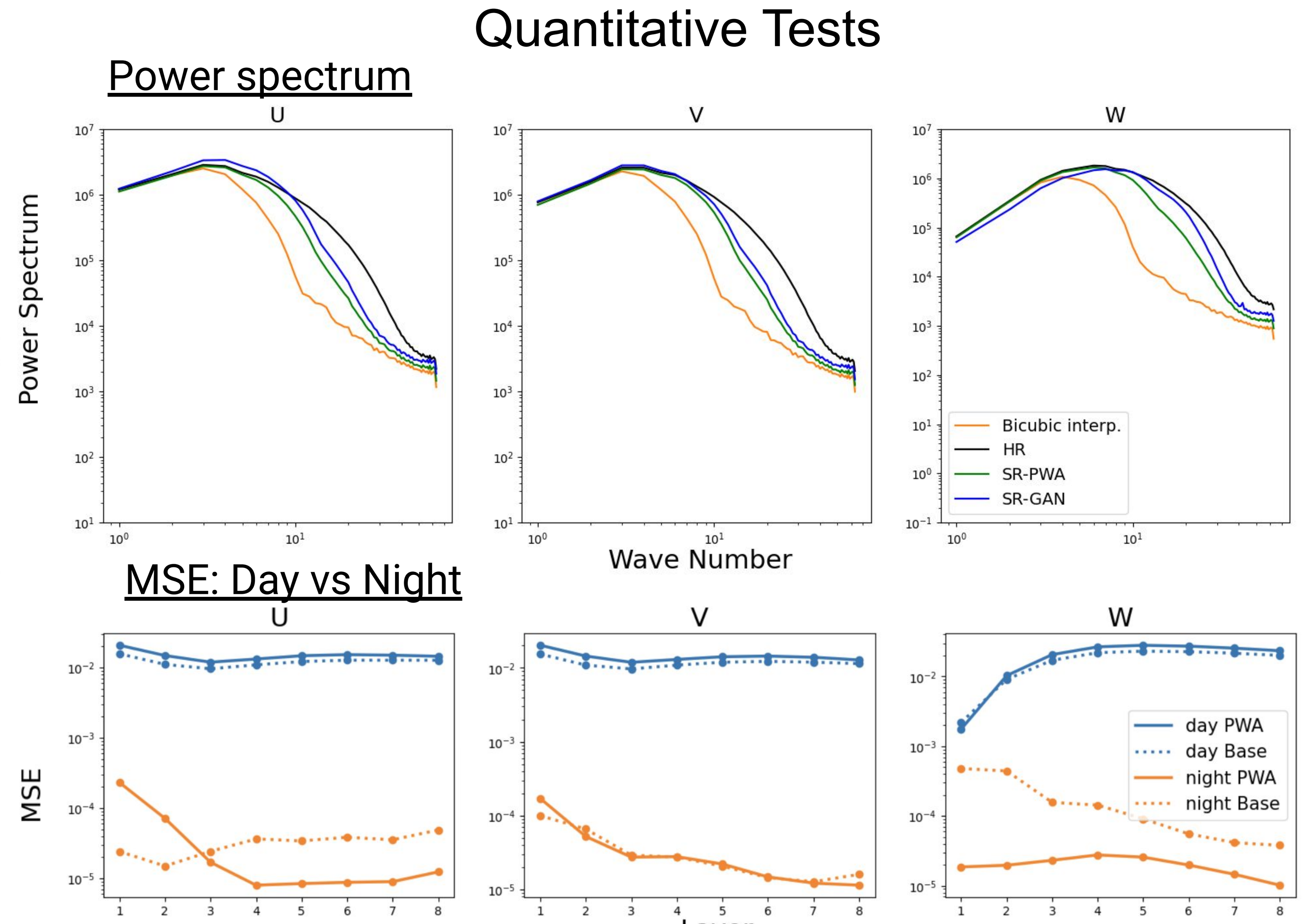


Preliminary results from PWA + GAN

Qualitative Test



Quantitative Tests



Takuya Kurihana

Acknowledgments: Supports for this work come from summer internship program at IBM Research, Yorktown Heights. The authors thank NeurIPS workshop committees to have opportunities to present our research outcomes.

Conclusion

This work show sour preliminary investigation of the super-resolution of 3D wind structures based on a newly developing SR network that utilizes a self-attention network and a generative model. It enables to incorporating of 3D dynamics of weather systems that are essential to reconstructing physically representative 3D wind fields, and then achieve to generate high-fidelity outputs.