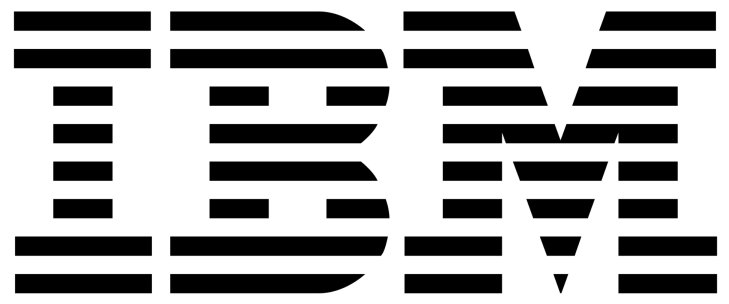




A 3D super-resolution of wind fields via physics-informed pixel-wise self-attention generative adversarial network

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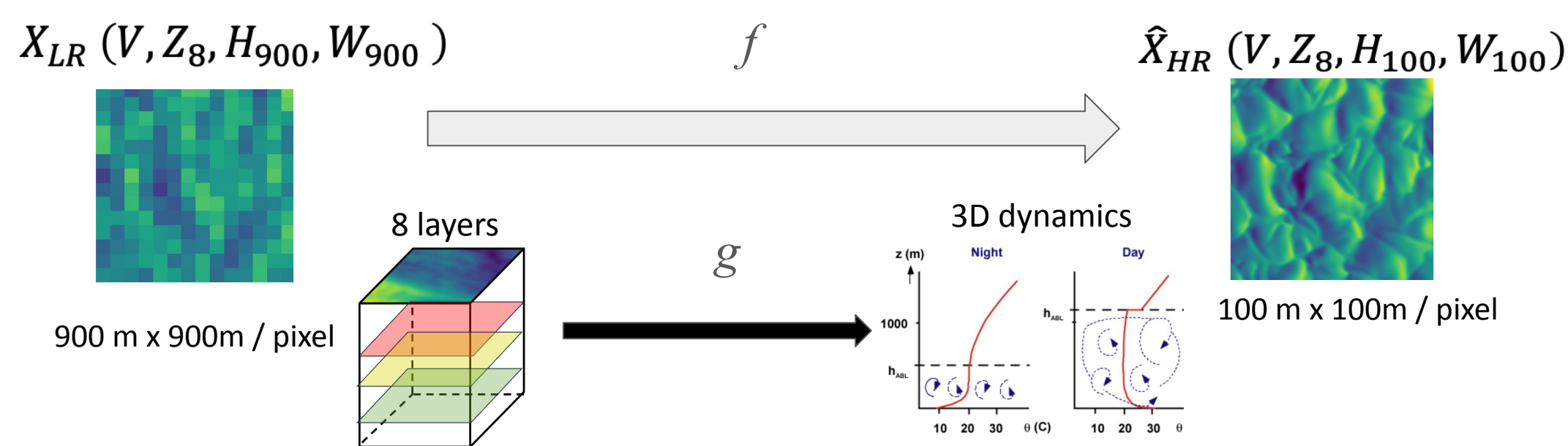


3D super-resolution of wind fields

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**

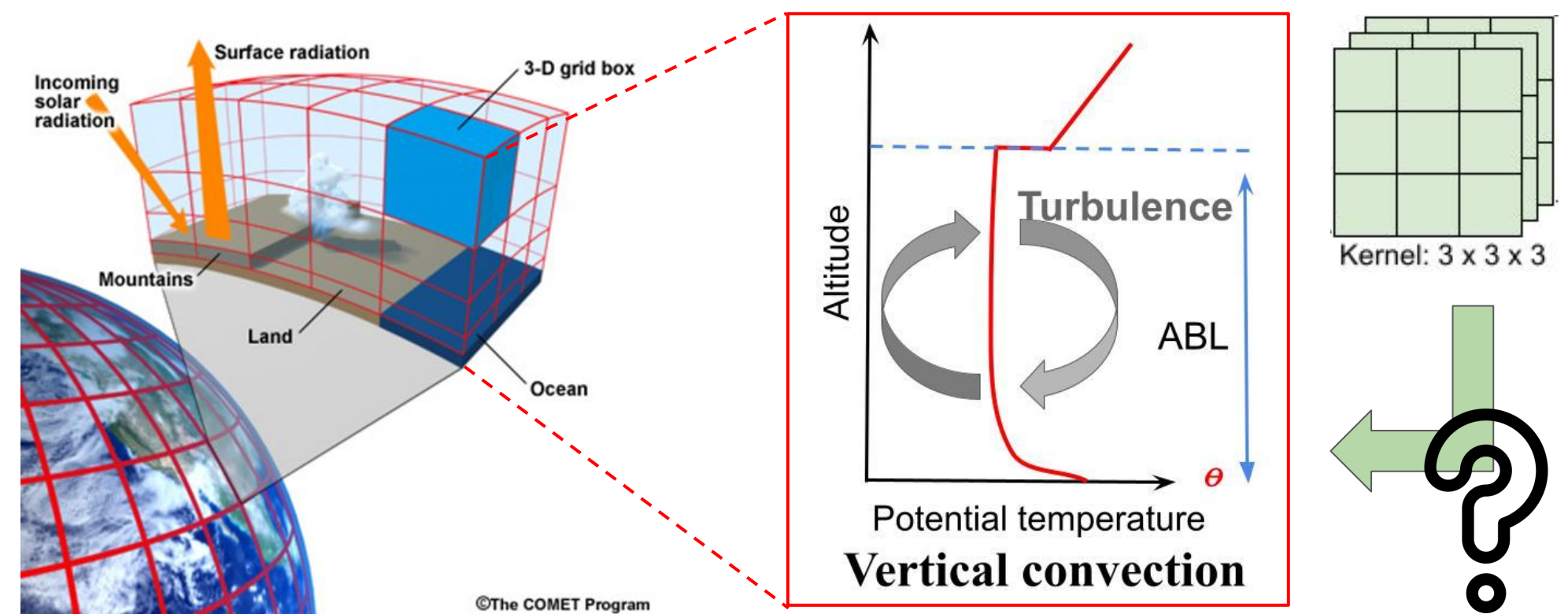
→ We need a **3D SR neural network f** , which learns **3D dynamics** via g !



Standard conv filters fall short in capturing physics

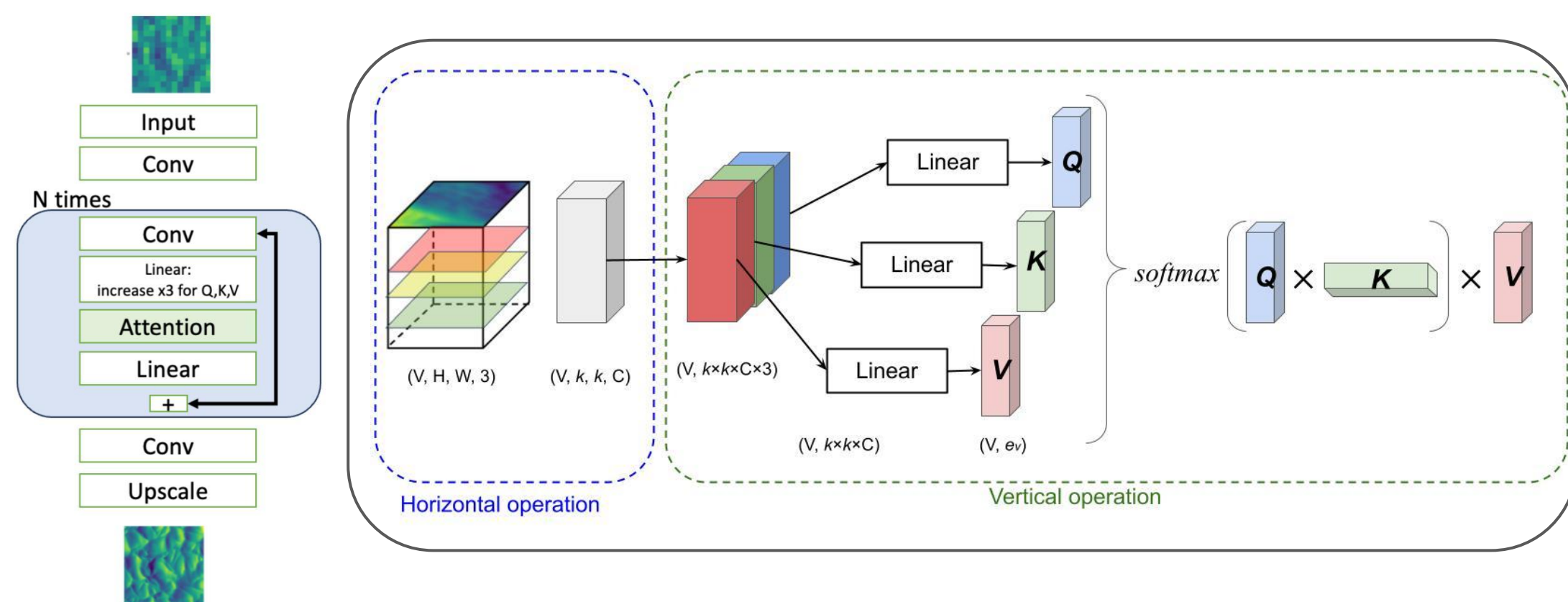
Issue:

- 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**

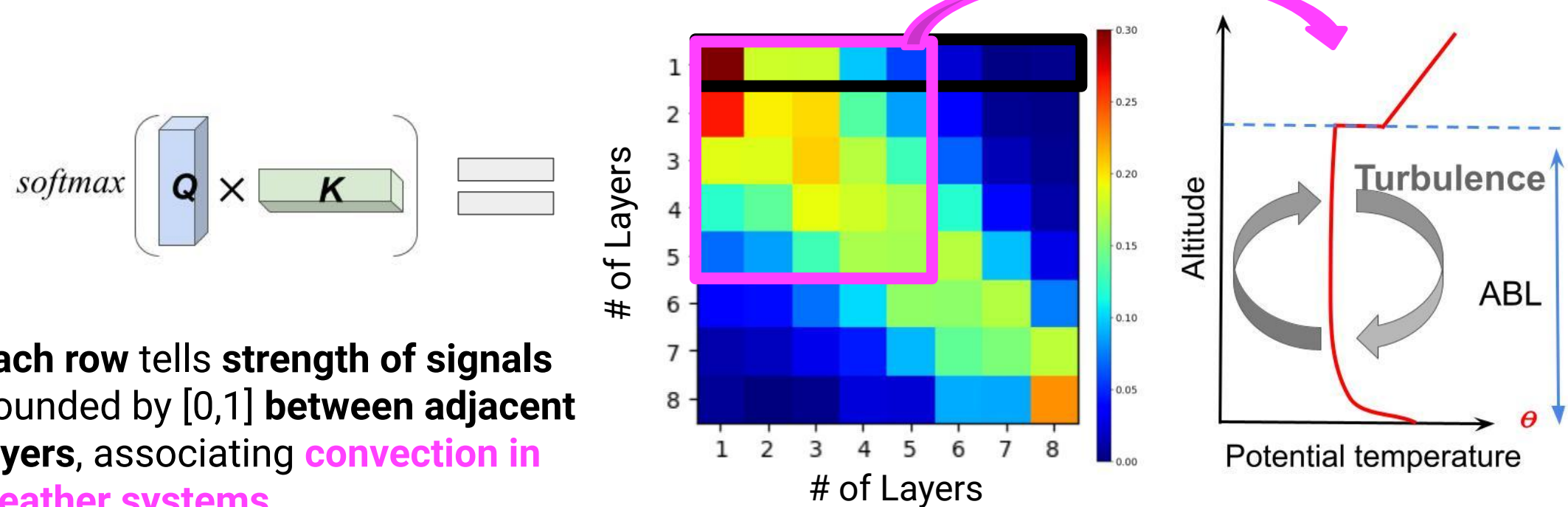


Pixel-Wise self-Attention Network: PWA Network

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 $R(M)$:

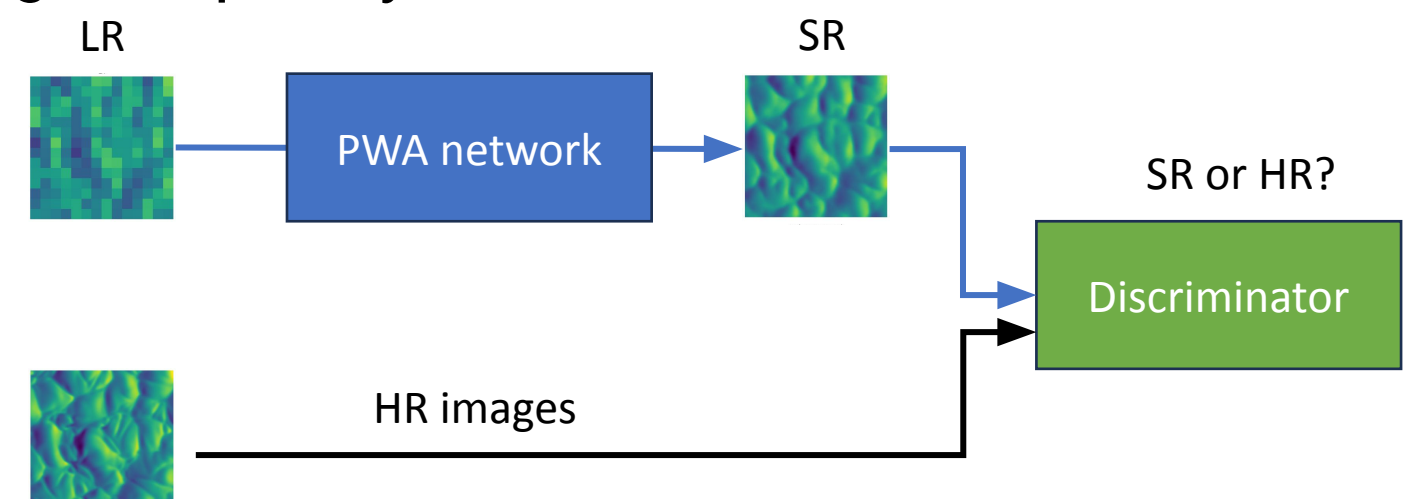
$$R_i = \sum_{j=1}^V M_{ij}^2,$$
$$R(M) = \sum_{i=1}^V \frac{1}{R_i},$$

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

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

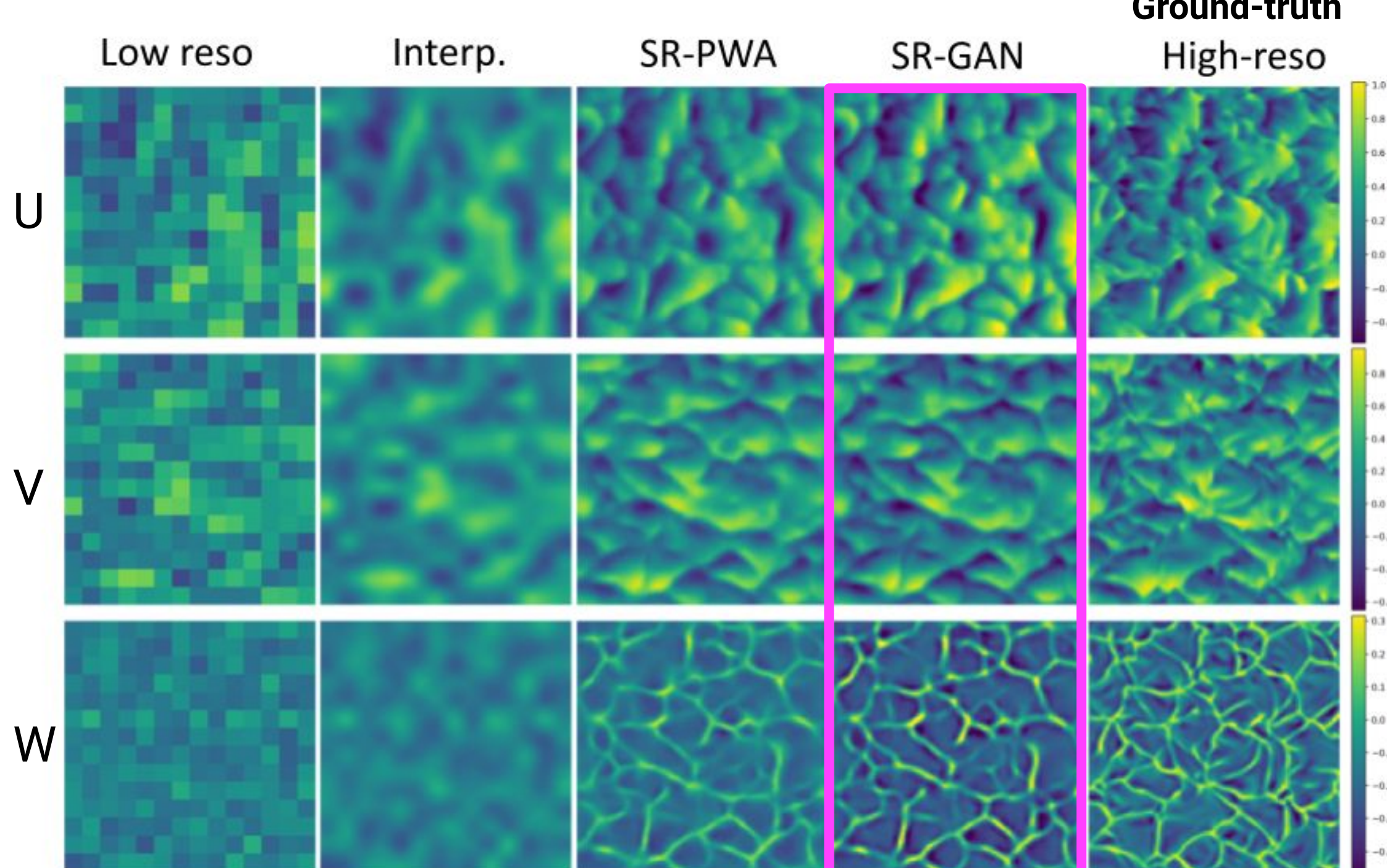
Generative Adversarial Network (GAN)

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

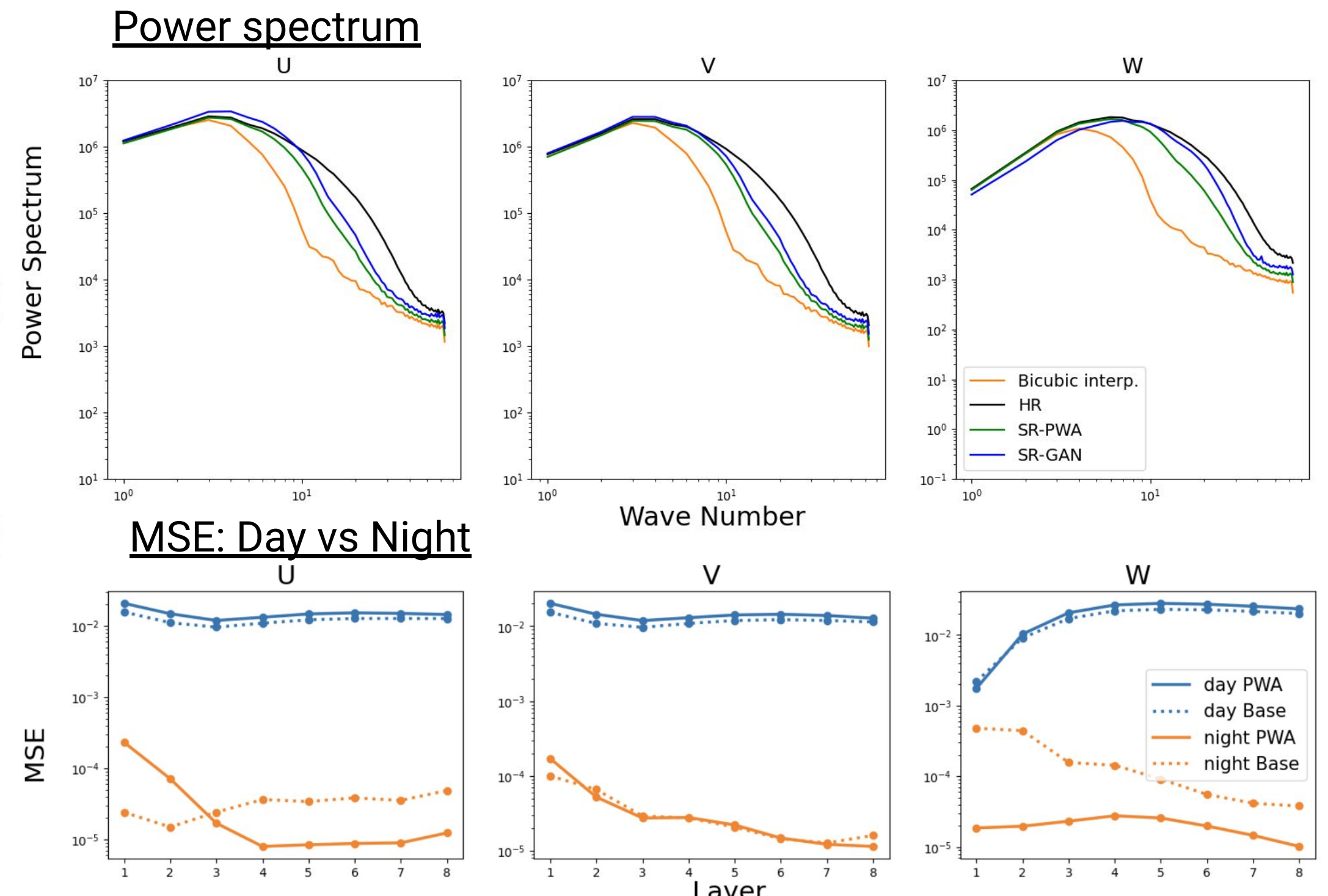


Preliminary results from PWA + GAN

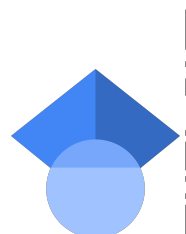
Qualitative Test



Quantitative Tests



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Conclusion

This work shows our 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 the incorporation of 3D dynamics of weather systems that are essential to reconstructing physically representative 3D wind fields, and then achieve to generate high-fidelity outputs.