Enhancing Renewable Energy Data with Deep Learning

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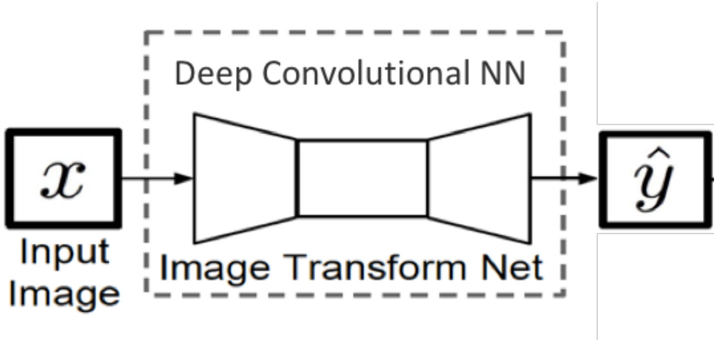
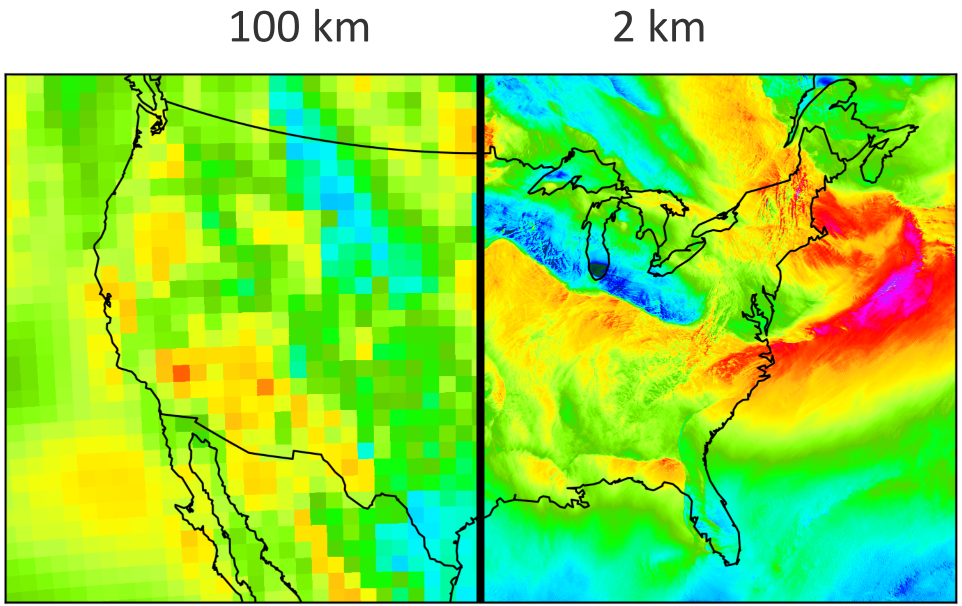
Climate Downscaling Challenge

Climate models are typically run at ~100km resolution, but ~2 km resolution is required for renewable energy resource assessments.

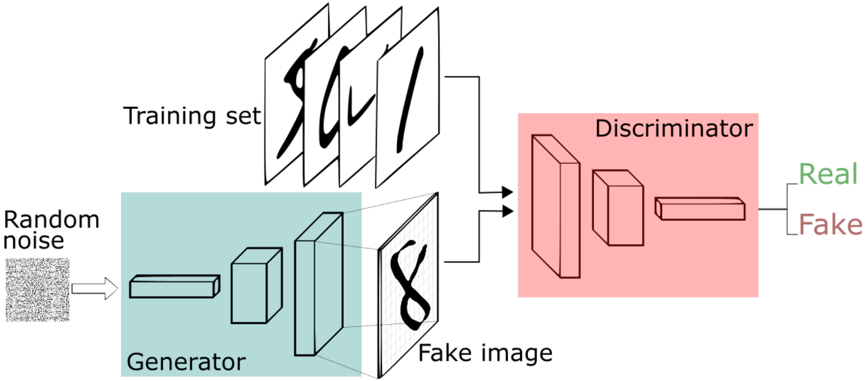
Can Scientific Machine Learning (SciML) help with downscaling?





Super resolution of climate data

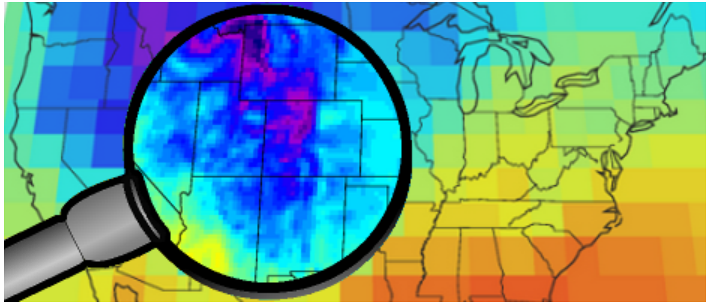
- Super resolution has been effective on natural images, can we use it to enhance scientific data?
- Approach: convolutional neural networks (CNN) + adversarial training



https://sthalles.github.io/intro-to-gans/

$$\min_G \max_D \mathbb{E}\left[\log\left(D(\mathbf{y})\right)\right] + \mathbb{E}\left[\log\left(1 - D(G(\mathbf{x}))\right)\right]$$

Ledig et al. 2017



https://www.gfdl.noaa.gov/climate-model-downscaling/

Using SR to Downscale GCM Data

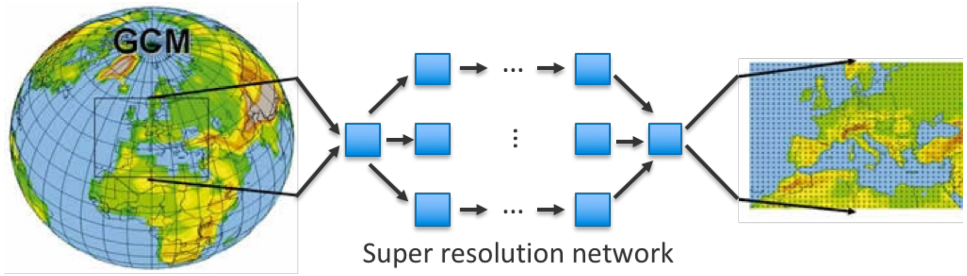
Training data: NREL's Wind Integration National Database Toolkit (WTK) and National Solar Radiation Database (NSRDB)

Testing data: NCAR's Community Climate System Model (CCSM) used in IPCC studies

Model	CCSM4	NSRDB	WIND Toolkit
Institute	NCAR	NREL	NREL
Data	wind & solar	solar	wind
Spatial Res.	0.9° lat $\times$ 1.25° lon	0.04°	$2\,km$
Years	2020-2039	2007-2013	2007-2013
Temporal Res.	daily average	hourly	4 hourly

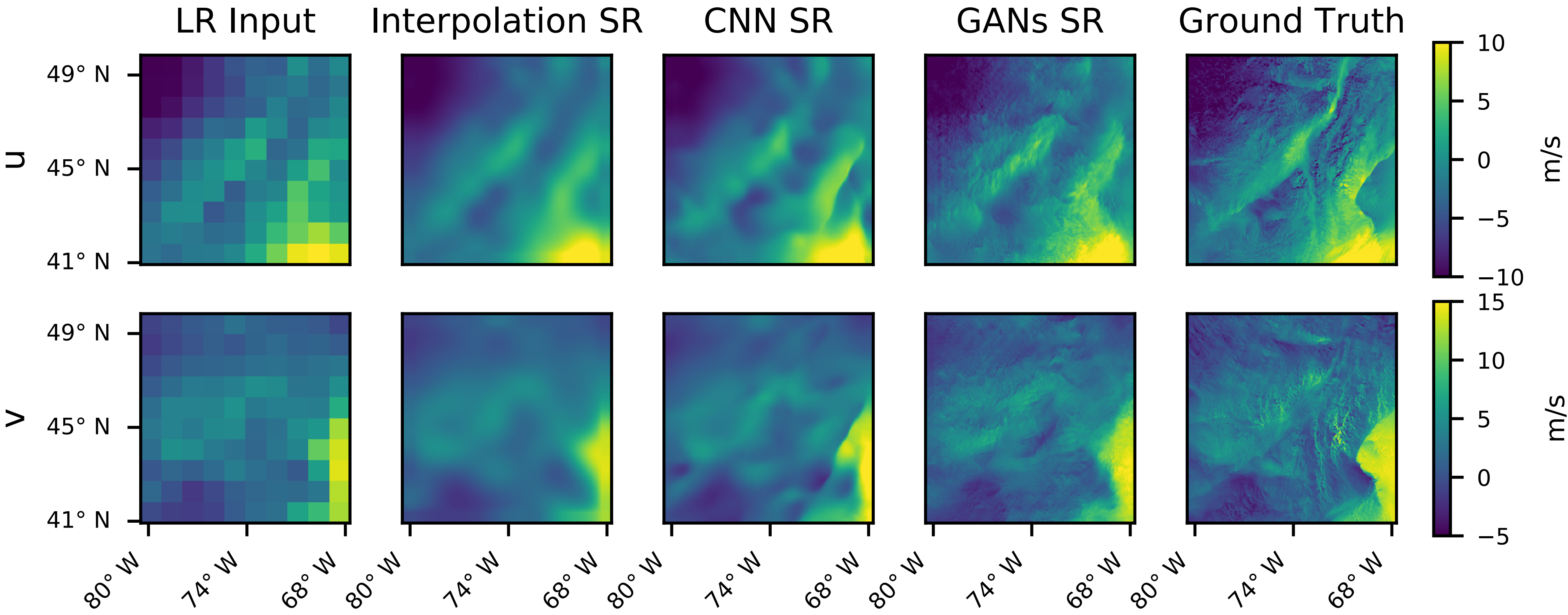
Process

1. Train super resolution networks on coarsened WTK/NSRDB data.
2. Apply the trained CNNs to super resolve CCSM wind/solar data.

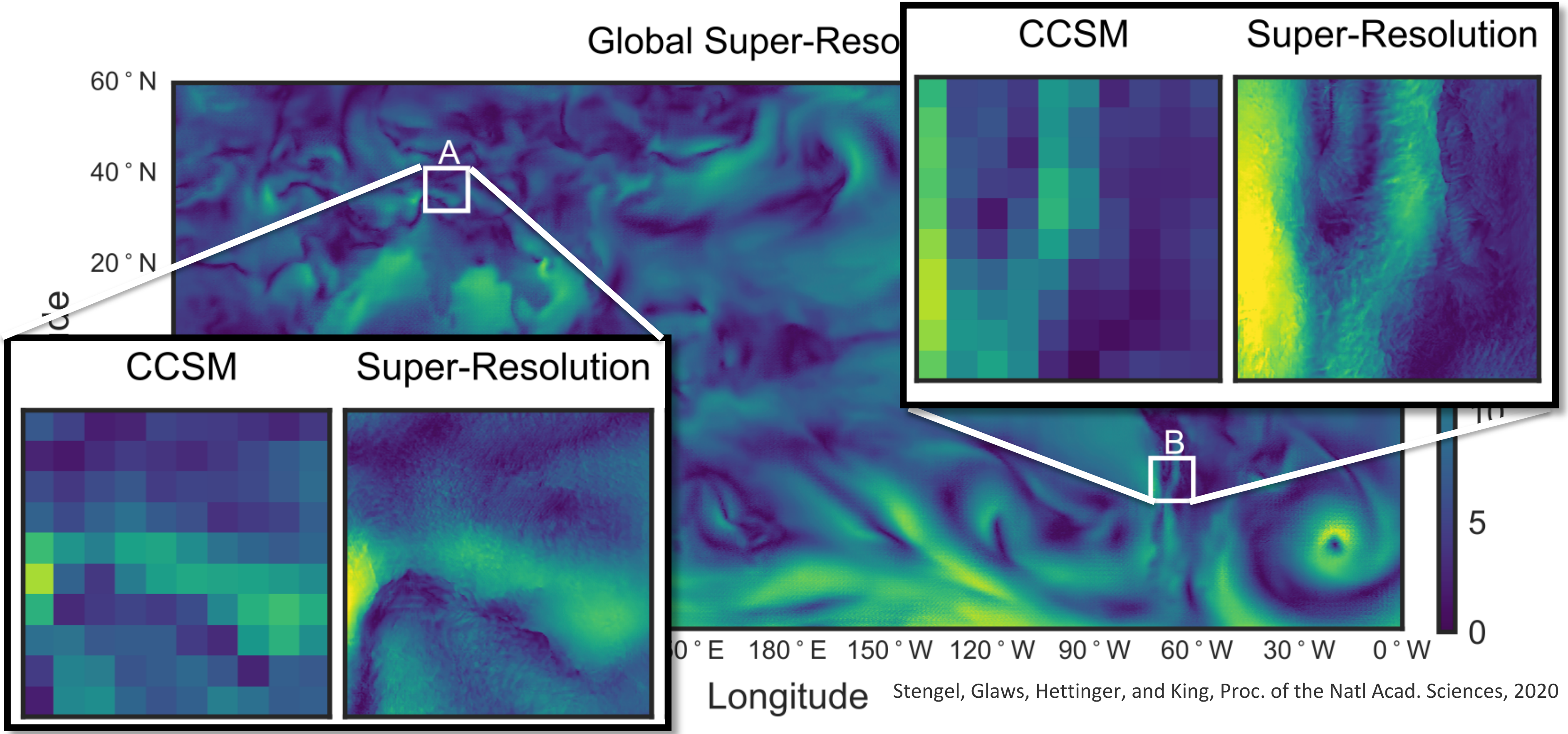


Testing the Trained Super Resolution Model

- Coarse 100km resolution wind data → WIND Toolkit 2 km resolution



Evaluating on Climate Data



Stengel, Glaws, Hettinger, and King, Proc. of the Natl Acad. Sciences, 2020

Quantifying Improvements in Generated Fields

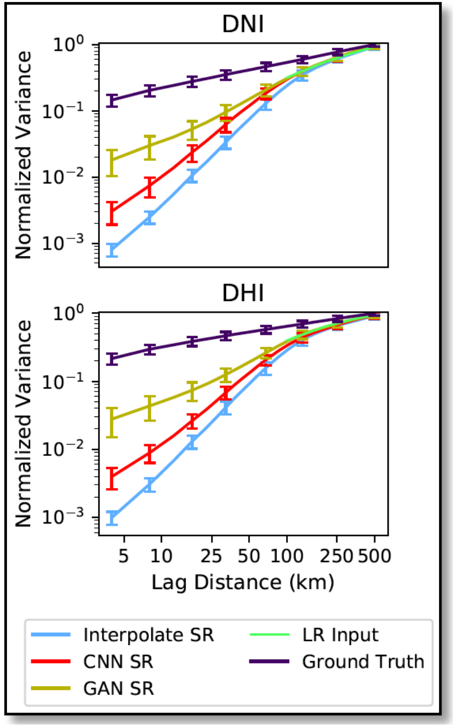
- Adversarial training produces quantifiable improvements in physical quality
  - Correct turbulent statistics
  - DNI & DHI semivariogram improved
- Perception/distortion tradeoff
  - Adversarial training increases MSE

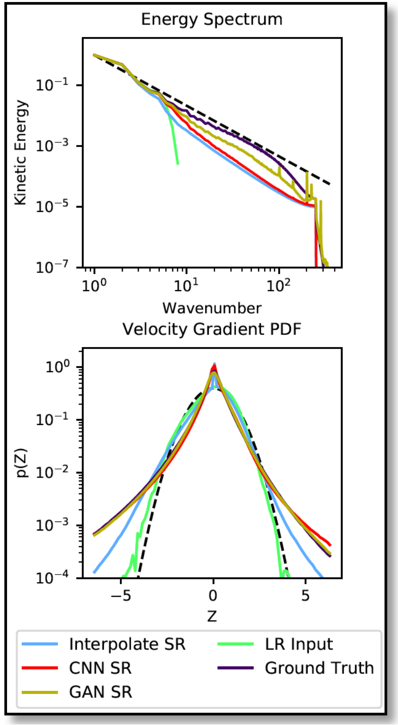
$$\mathcal{L}_G(\mathbf{x}, \mathbf{y}) \;=\; \mathcal{L}_{content}(\mathbf{x}, \mathbf{y}) + \alpha\, \mathcal{L}_{adversarial}(\mathbf{x}, \mathbf{y})$$

Mean Squared Error on Test Set

Quantity	Bicubic Interpolation	Pretraining	Adversarial
u	0.205	0.135	0.157
v	0.265	0.168	0.193

Quantity	Bicubic Interpolation	Pretraining	Adversarial
DNI	0.155	0.078	0.086
DHI	0.135	0.073	0.085



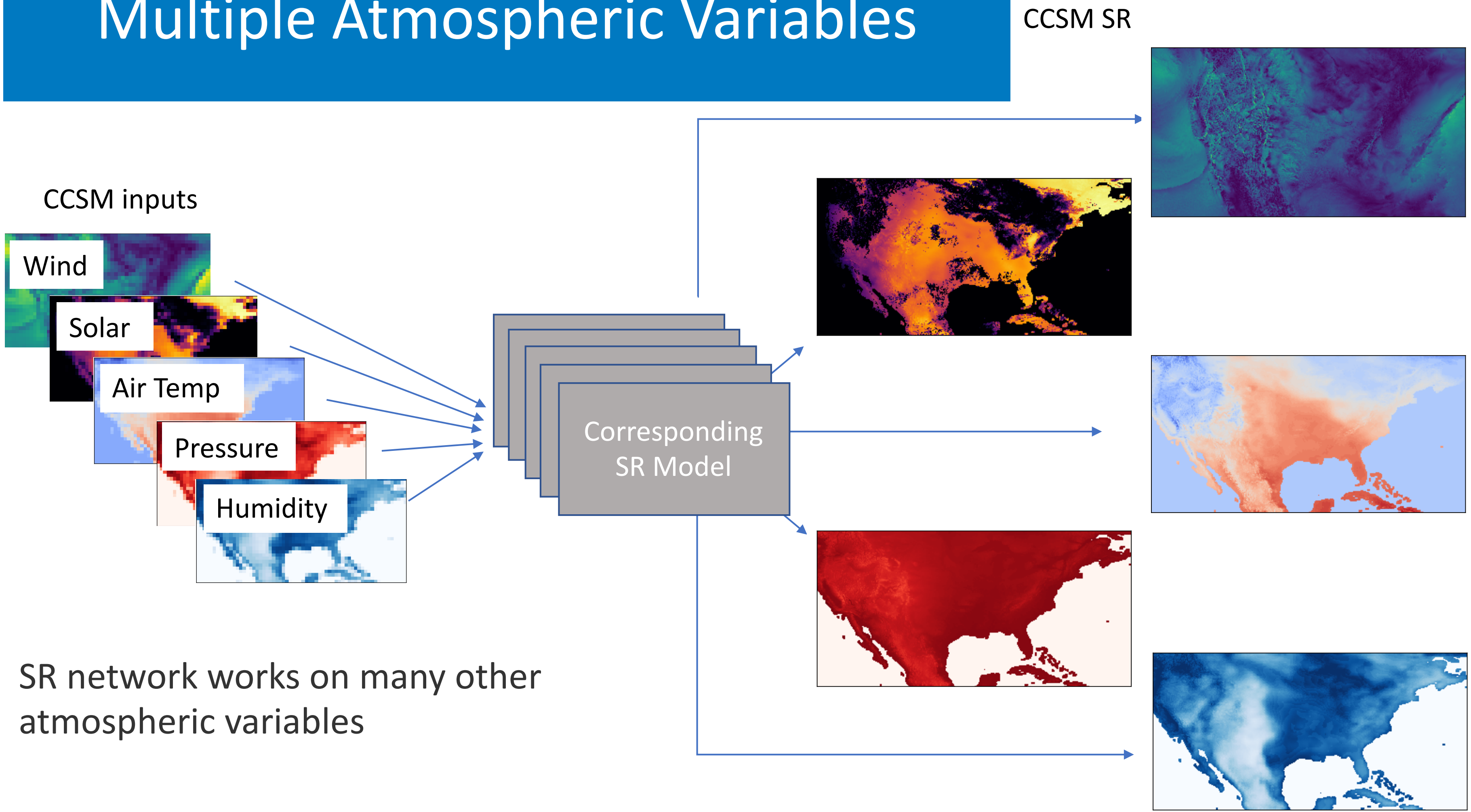


Stengel, Glaws, Hettinger, and King, Proc. of the Natl Acad. Sciences, 2020

Outcomes

- 50x resolution enhancement of wind and 25x resolution enhancement of solar data from IPCC 5th Assessment Report
- Fully trained network is open source: https://github.com/NREL/phire
- Recently accepted in PNAS, several other papers in review
- Extensions
  - Enhancing other atmospheric variables
  - Spatial and temporal super resolution
  - Generating multiple SR realizations

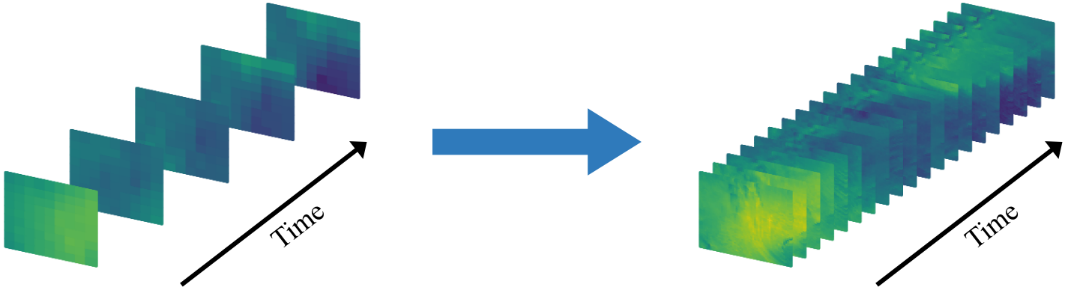
Multiple Atmospheric Variables



SR network works on many other atmospheric variables

Spatiotemporal Super Resolution

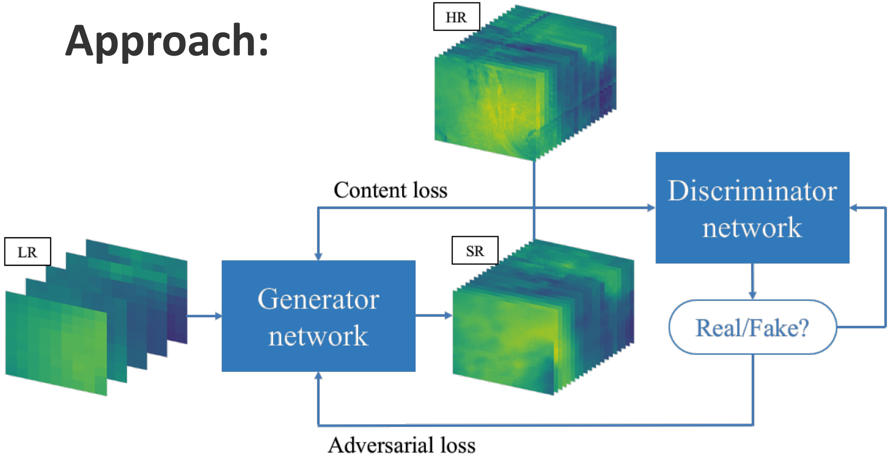
Goal: extend methods for enhancing spatial resolution of climate data to temporal domain



Daily -> hourly or

hourly -> 5 minute

Approach:



Challenges:

- Significant increase in enhanced details

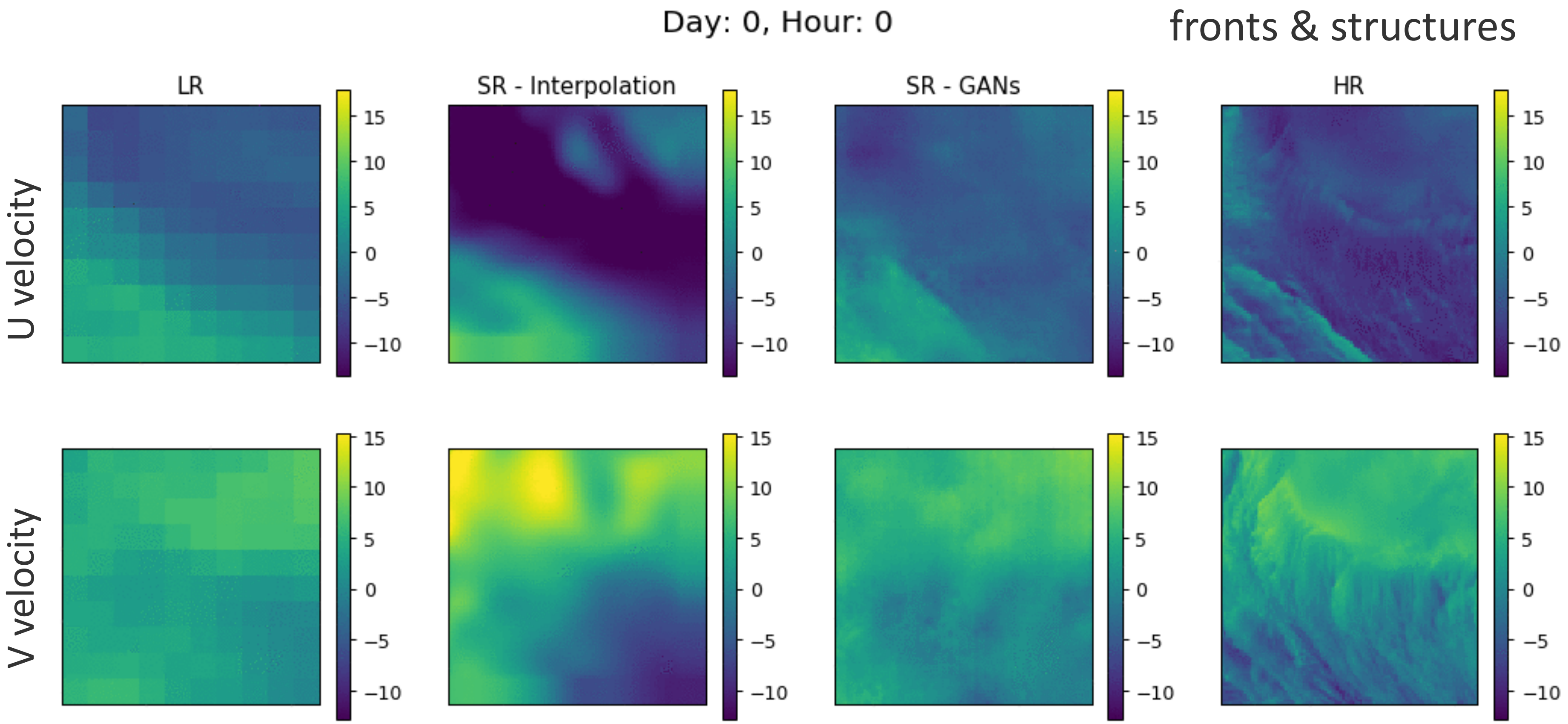
$$10 \times 10 \times 24 \text{ SR} \longrightarrow \frac{2{,}400 \text{ SR pixels}}{1 \text{ LR pixel}}$$

- Memory constraints require smaller batch sizes
- Must preserve temporal enhancement in a 2nd resolution jump

Spatiotemporal Super Resolution

Temporally coherent

Realistic advection of fronts & structures



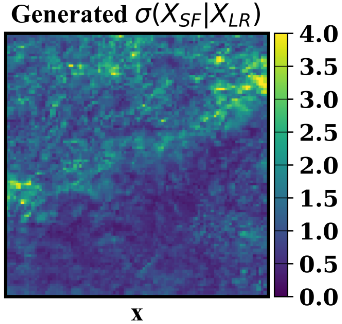
Generating Multiple Output Realizations

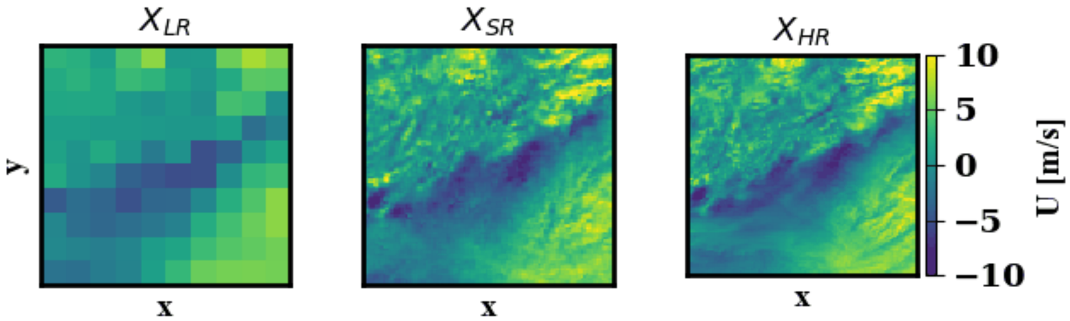
- What if we want to generate multiple SR realizations corresponding to the same low resolution input?
  - Importance sampling, extreme events, propagating uncertainty, etc

- Add a term to generator loss that encourages diversity of small scales X_{SF}

$$\mathcal{L}_G = \alpha\mathcal{L}_{con} + \beta\mathcal{L}_{adv} + \gamma\mathcal{L}_{div}$$

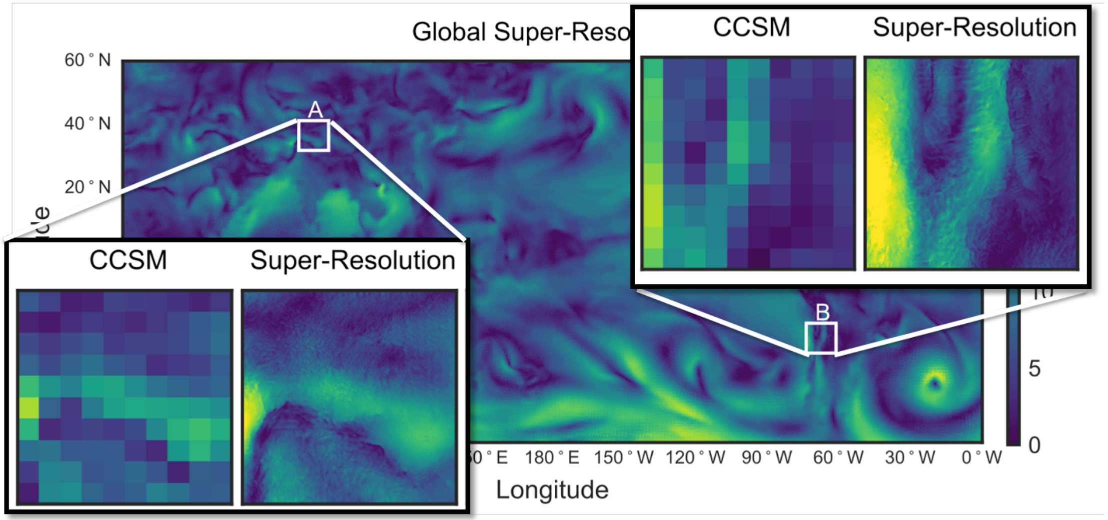
$$X_{HR} = X_{LR} + X_{SF}$$





Summary

- Created a physics-preserving adversarial super resolution tool with up to 50x enhancement of various atmospheric data
- Applicable to arbitrary sized input data (local/regional/global)
- Can simultaneously enhance resolution temporally and spatially
- Can generate multiple SR realizations for probabilistic forecasts, sampling extreme events, UQ, etc



Questions?

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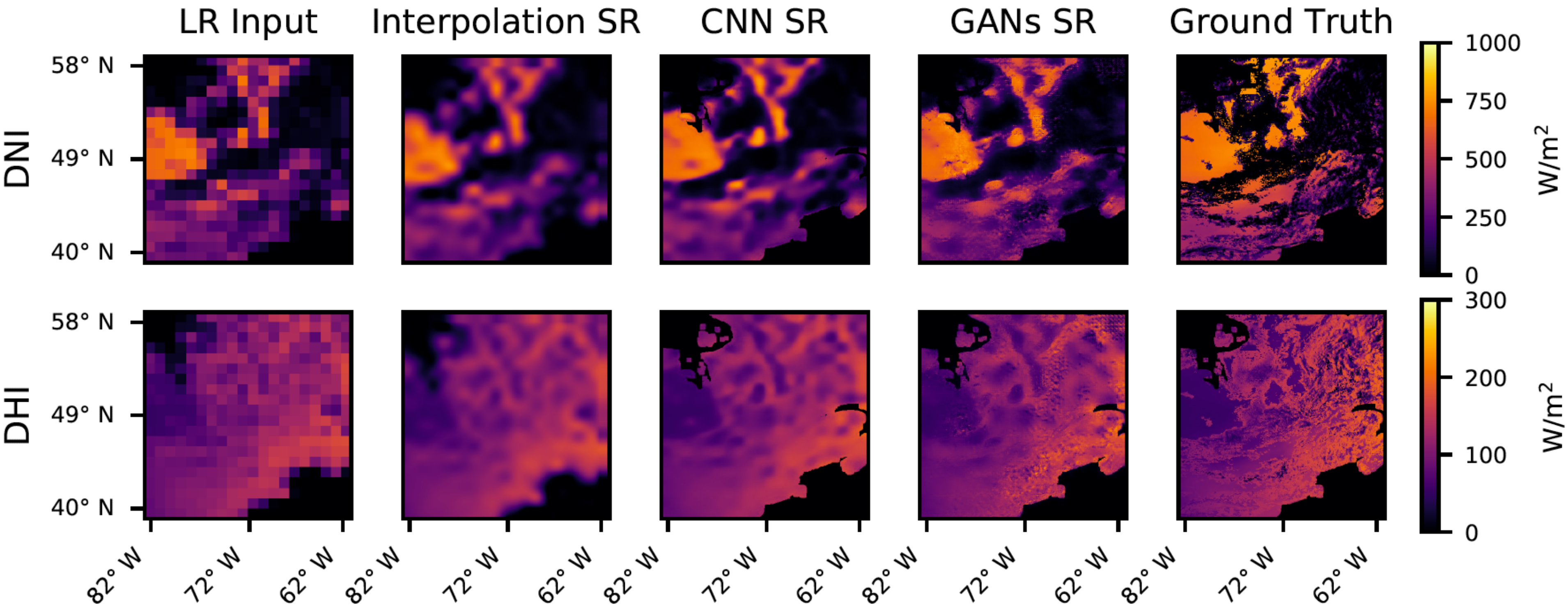
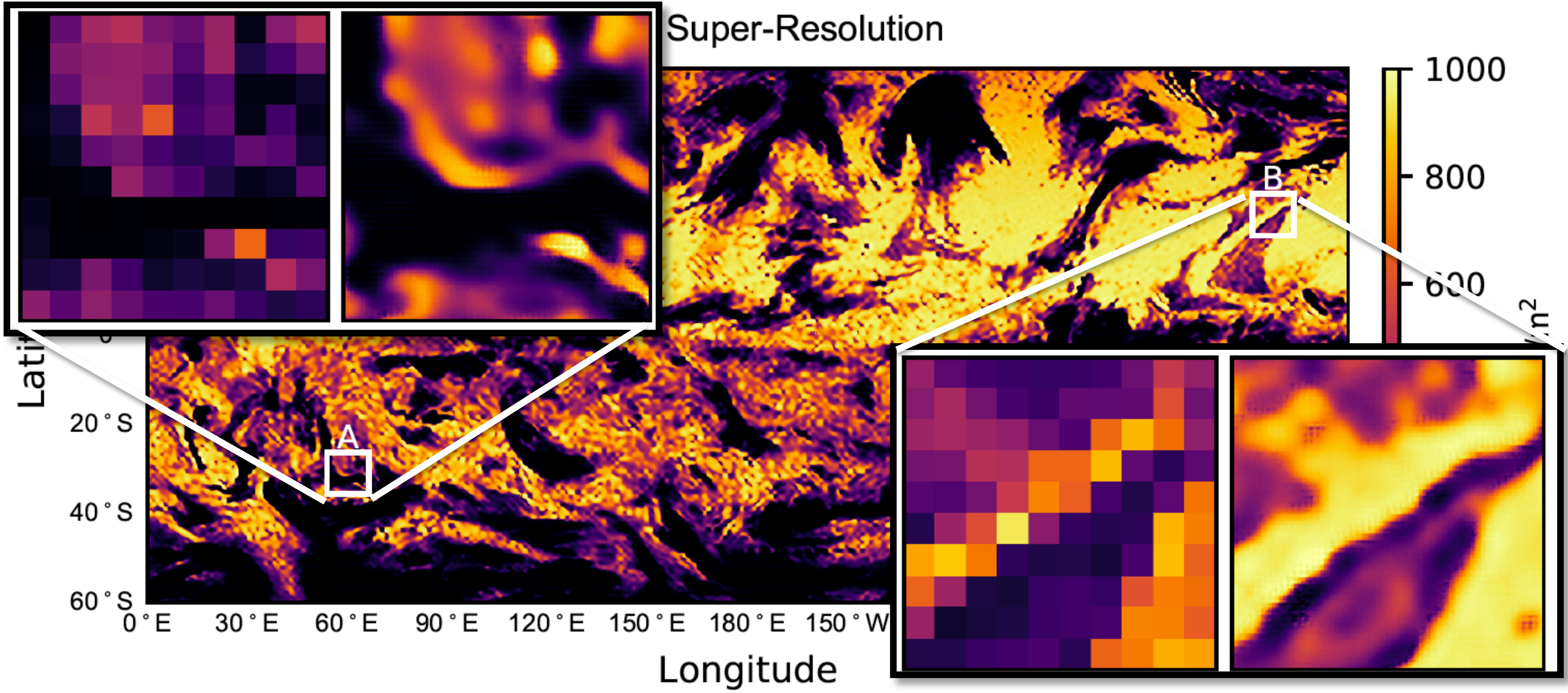
Testing the Trained Super Resolution Model

- Coarse 100km resolution solar data → NSRDB 4 km resolution

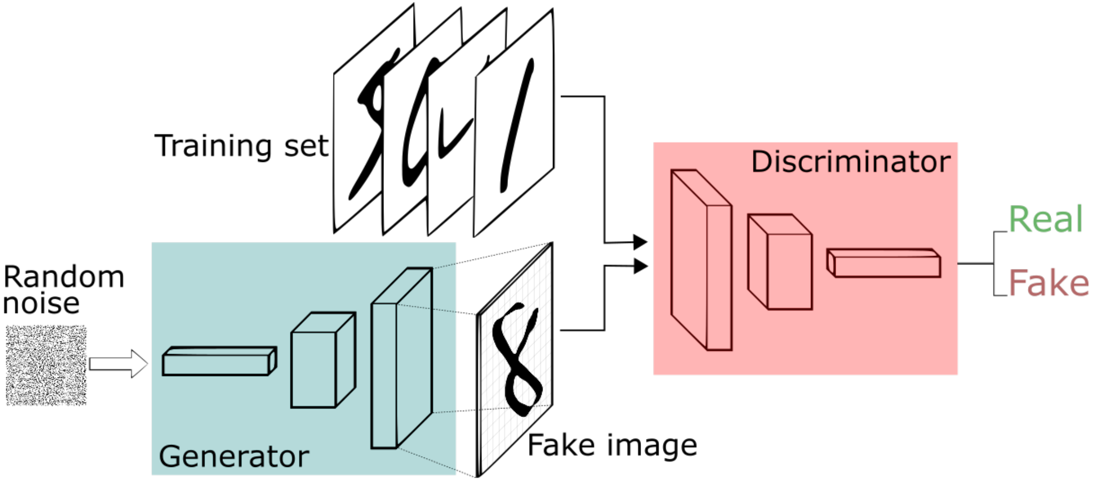


Global Solar Super Resolution



Generative Adversarial Networks (GAN)

- Train two competing neural networks: **generator** and **discriminator**
- Deep Learning + Game Theory = new ways to draw cats



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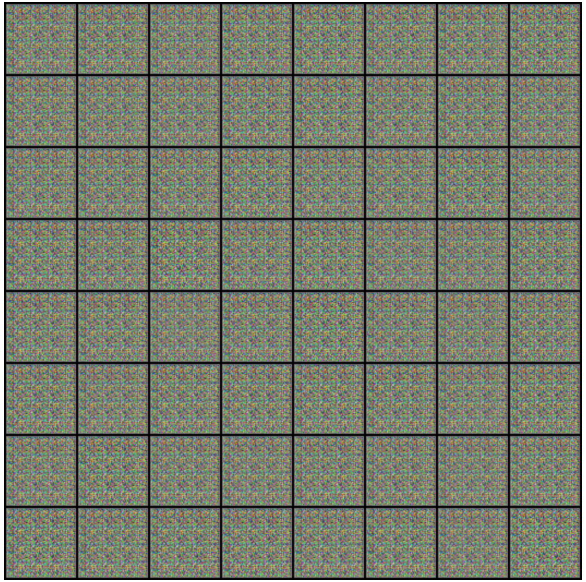
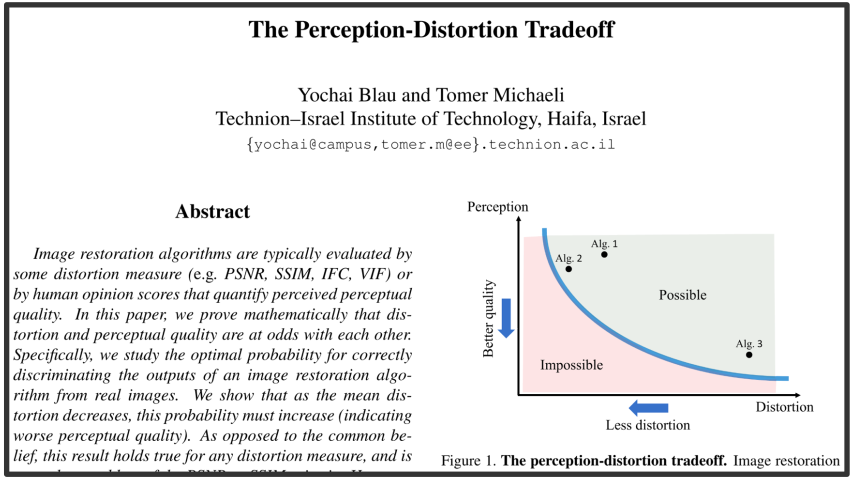
$$\min_G \max_D \mathbb{E}\left[\log\left(D(\mathbf{y})\right)\right] + \mathbb{E}\left[\log\left(1 - D(G(\mathbf{x}))\right)\right]$$

https://github.com/AlexiaJM/Deep-learning-with-cats



Training the Super-Resolution Network

- Interpolation and CNN's alone produce fields with **low distortion** that are too smooth.
- Adversarial training improves **perceptual quality** but introduces distortion.
- Perception-distortion tradeoff



The Perception-Distortion Tradeoff

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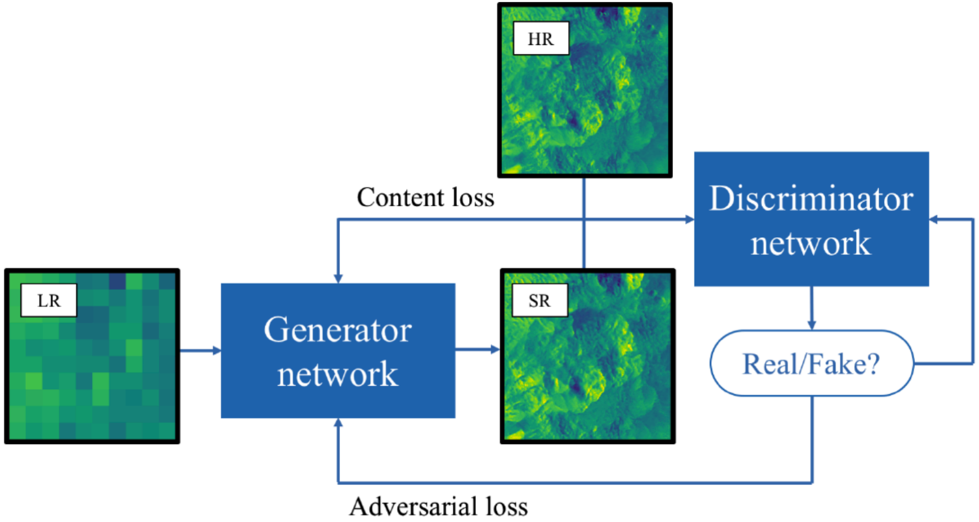
Abstract

Image restoration algorithms are typically evaluated by some distortion measure (e.g. PSNR, SSIM, IFC, VIF) or by human opinion scores that quantify perceived perceptual quality. In this paper, we prove mathematically that distortion and perceptual quality are at odds with each other. Specifically, we study the optimal probability for correctly discriminating the outputs of an image restoration algorithm from real images. We show that as the mean distortion decreases, this probability must increase (indicating worse perceptual quality). As opposed to the common belief, this result holds true for any distortion measure, and is

Figure 1. **The perception-distortion tradeoff.** Image restoration



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Two-step Super Resolution

Two separate networks manages complexity, speeds up training and avoids vanishing gradients

Networks take ~3 days to train on 1 GPU with ~40k training images

Networks can generate ~400 images in < 5 minutes