AI/ML as a gateway to design with HFM

Ryan King, PhD

Senior Scientist, Computational Science Center NREL

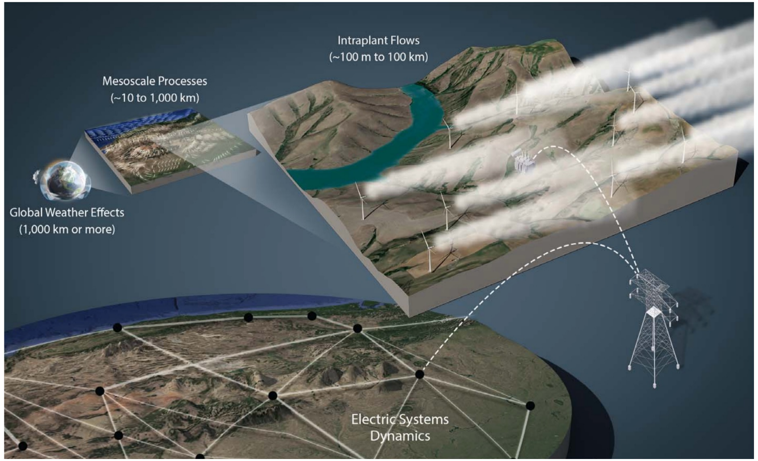
6th Wind Energy Systems Engineering Workshop

August 31st, 2022

AI/ML Achieving Wind Energy Goals

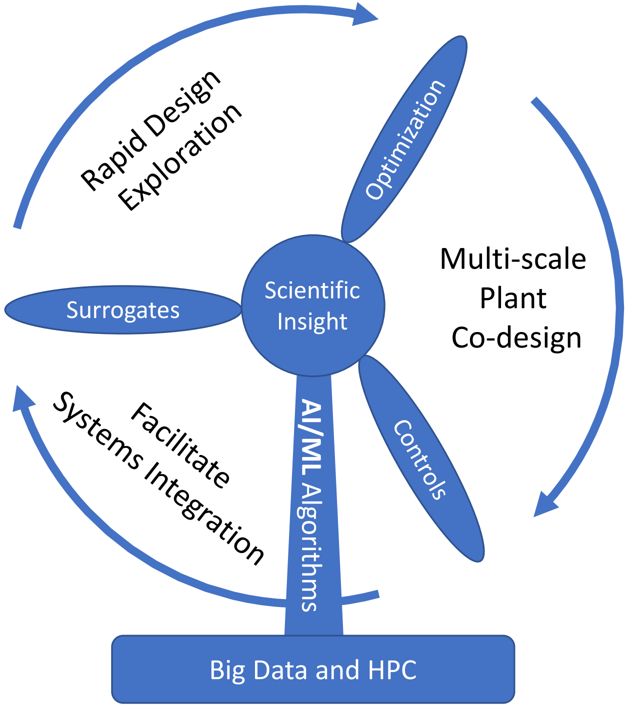
Biden administration goal: **100% carbon-free electricity by 2035**

Artificial intelligence and machine learning (AI/ML) provide new pathways to improve planning, design, and controls that can help achieve 2035 goals.



Veers et al, Grand challenges in the science of wind energy. Science, 2019

AI/ML in Wind

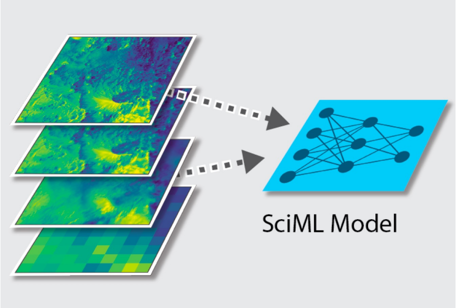


A New AI/ML Modeling Paradigm

- High fidelity modeling (HFM) codes are often too expensive for design, optimization, or controls

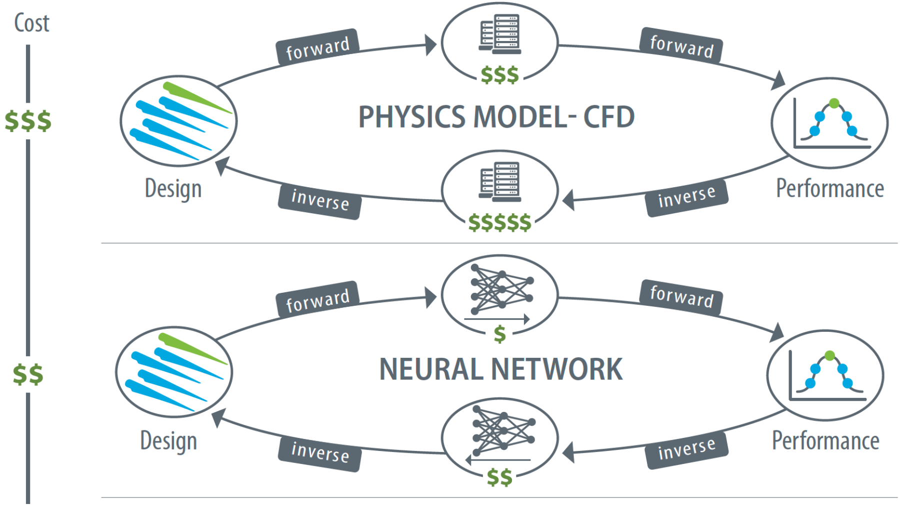
- Existing reduced order models are inaccurate for nonlinear dynamics arising in large and flexible turbines

- AI/ML models trained on HFM data encode HFM accuracy at low cost



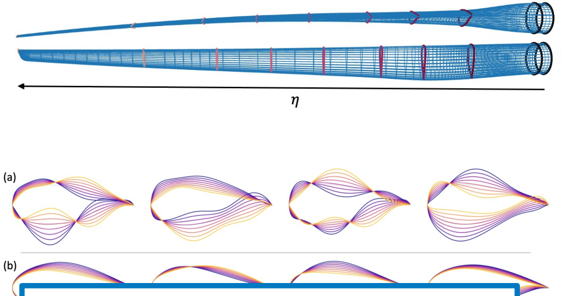
HFM data used to train ML model

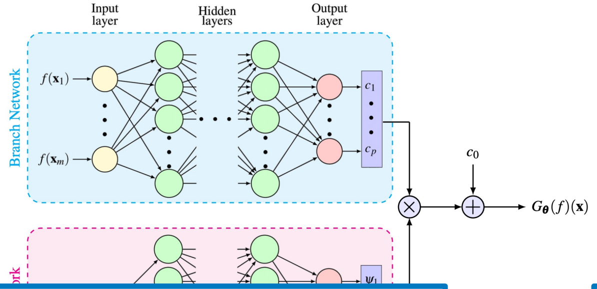
Expensive CFD design loop

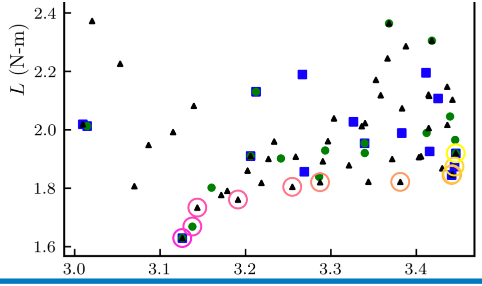


Accelerated ML design loop

AI/ML Themes in Computational Workflows







Domain Data

- Data representation
- Dimension reduction and data compression
- Sampling and experimental design

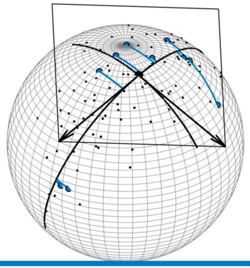
Forward Process

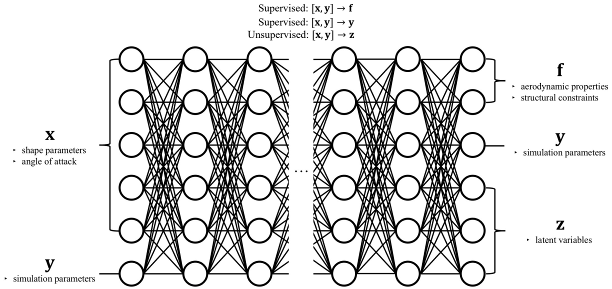
- Problem formulation
- Numerical model
- Physical experiment
- Surrogate modeling
- Hybrid physics + data

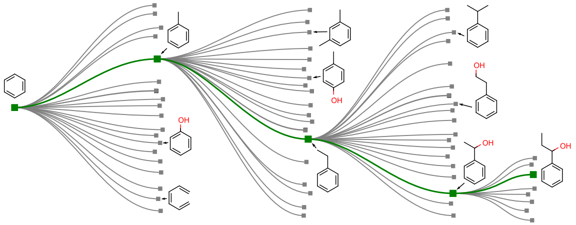
Outer Loop Problems

- Controls/decision-making
- Inference
- Uncertainty quantification
- Sensitivity analysis
- Optimization

Categories of Scientific AI/ML Models







Unsupervised Learning

- Finds structure in untagged data
- Data compression, anomaly detection, pattern recognition
- Sampling and generative models

Insight

Supervised Learning

- Learns input/output maps
- Can encode problem physics
- Performance (usually) scales with amount of training data

Prediction

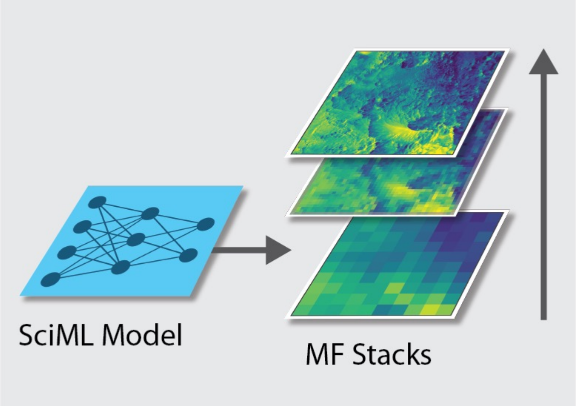
Reinforcement Learning

- Sequential decision making to maximize a reward
- Exploration/exploitation
- Model-based or model-free

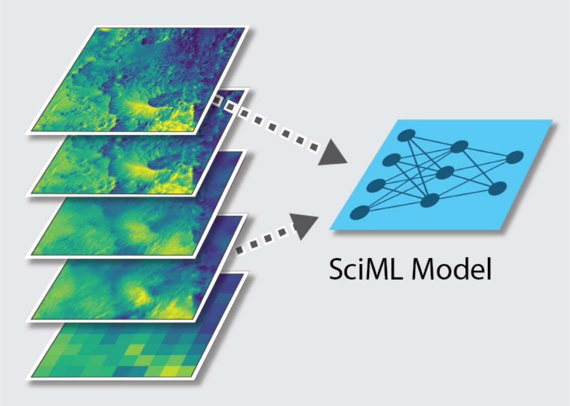
Action

AI/ML in a Multifidelity Context

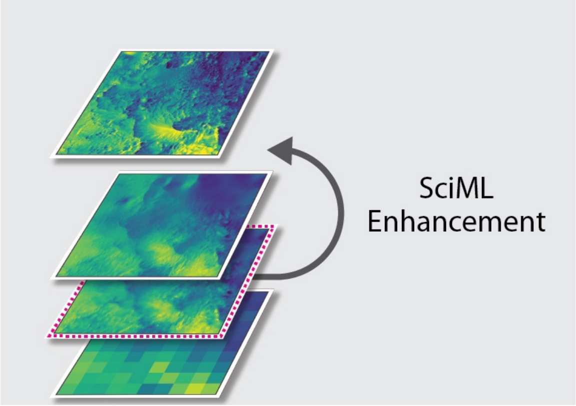
AI/ML model in a multifidelity hierarchy



Training AI/ML model with multifidelity data

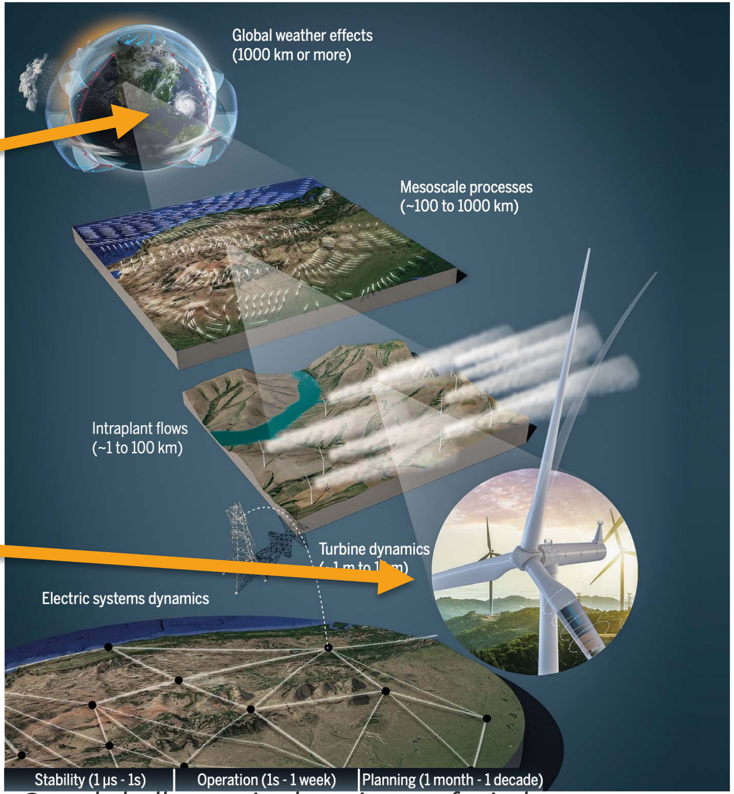


AI/ML to enhance a model's fidelity



Successful AI/ML Applications Across Wind Lifecycle

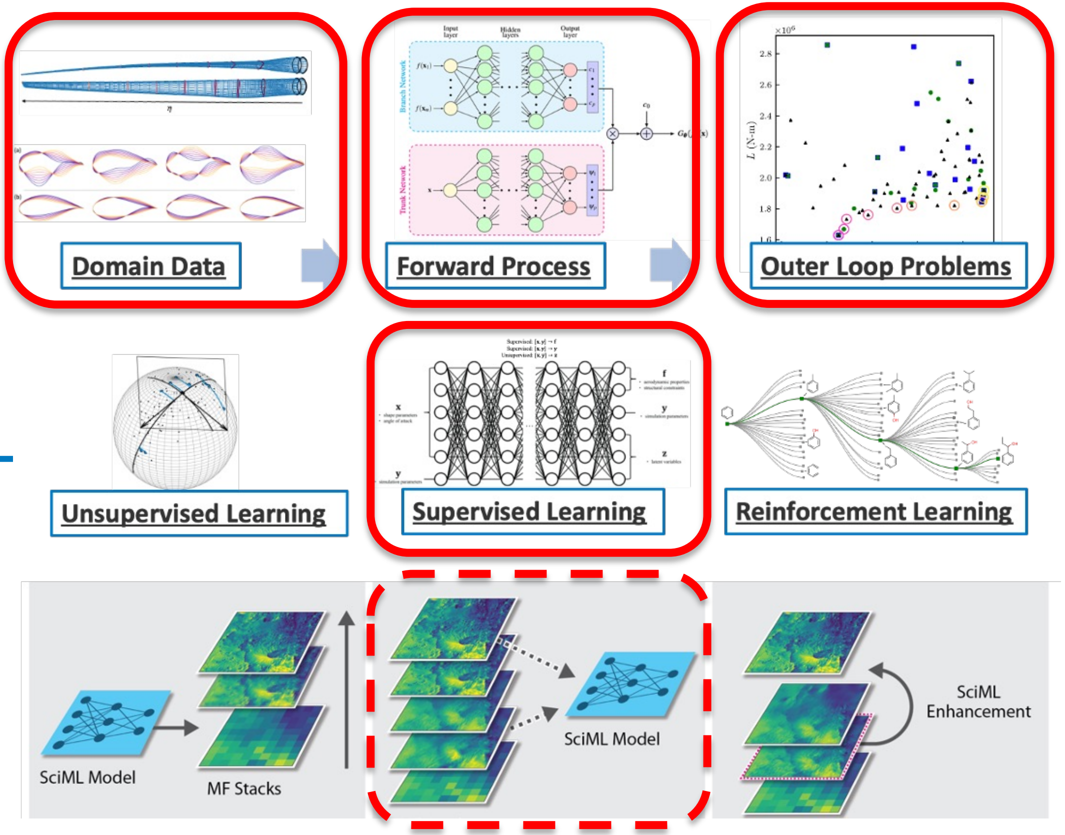
- Case Study: Resource Assessment
- Too many others to cover today
- Case Study: Blade Design



Grand challenges in the science of wind energy. Veers et al, Science, 2019.

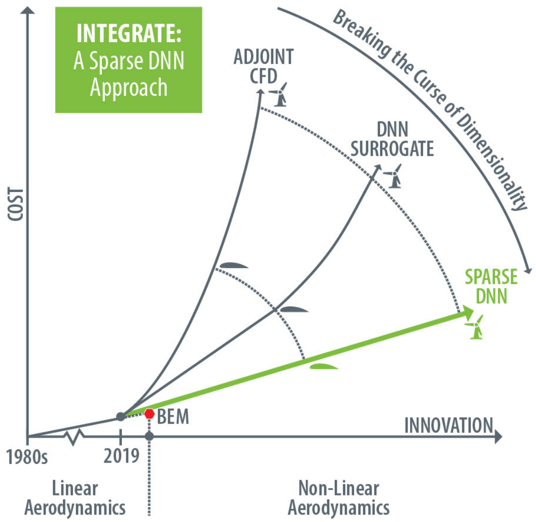
Example #1
Inverse Blade Design

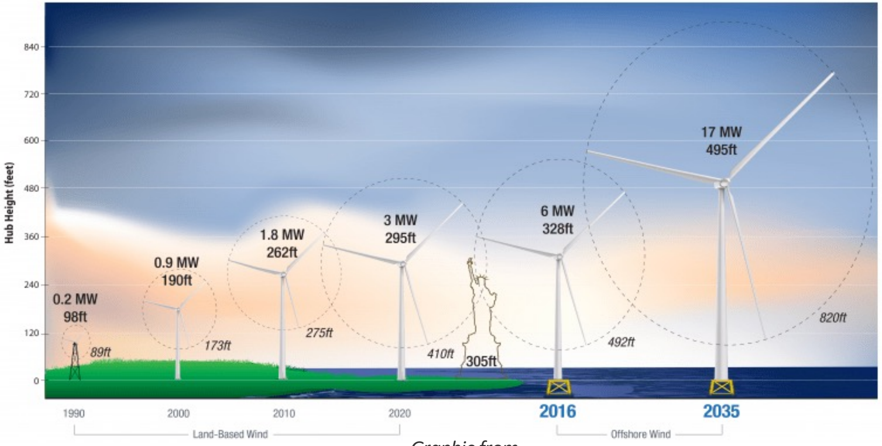
Collaborators: Ganesh Vijayakumar, Andrew Glaws, Zach Grey, Olga Doronina, Bum Seok Lee, James Baeder



Wind Turbine Blade Design

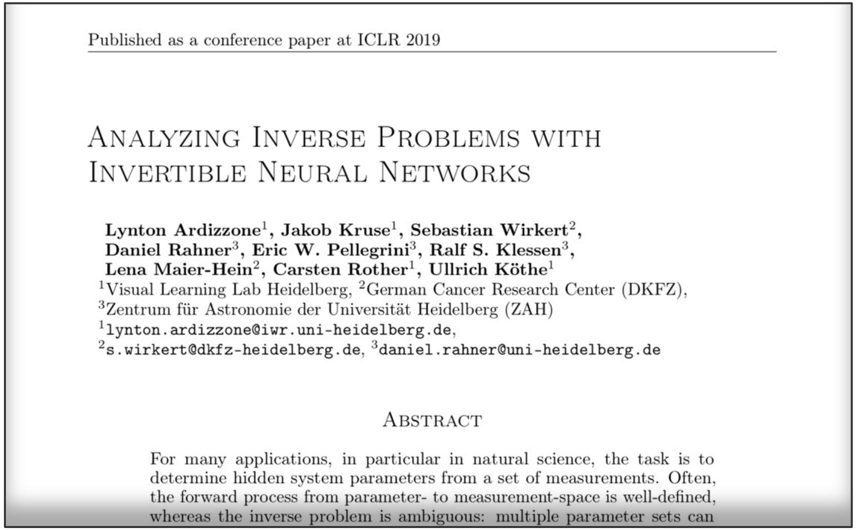
- Wind turbines are becoming taller and larger.
- Linearized blade element momentum (BEM) techniques fail to capture 3D nonlinear aerodynamics.
- Design optimization with 3D unsteady CFD is expensive, even with adjoint gradient capability.
- Can we solve this as an inverse problem with AI/ML?





Graphic from

Inverse Design Problem



Published as a conference paper at ICLR 2019

ANALYZING INVERSE PROBLEMS WITH INVERTIBLE NEURAL NETWORKS

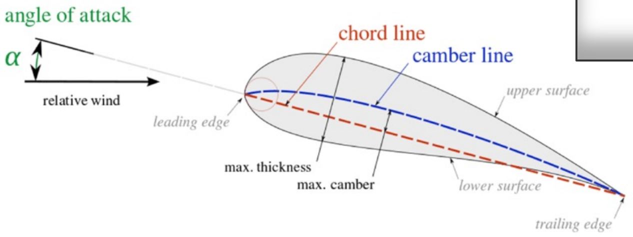
Lynton Ardizzone[1], Jakob Kruse[1], Sebastian Wirkert[2], Daniel Rahner[3], Eric W. Pellegrini[3], Ralf S. Klessen[3], Lena Maier-Hein[2], Carsten Rother[1], Ullrich Köthe[1]
[1]Visual Learning Lab Heidelberg, [2]German Cancer Research Center (DKFZ), [3]Zentrum für Astronomie der Universität Heidelberg (ZAH)
[1]lynton.ardizzone@iwr.uni-heidelberg.de, [2]s.wirkert@dkfz-heidelberg.de, [3]daniel.rahner@uni-heidelberg.de

ABSTRACT

For many applications, in particular in natural science, the task is to determine hidden system parameters from a set of measurements. Often, the forward process from parameter- to measurement-space is well-defined, whereas the inverse problem is ambiguous: multiple parameter sets can

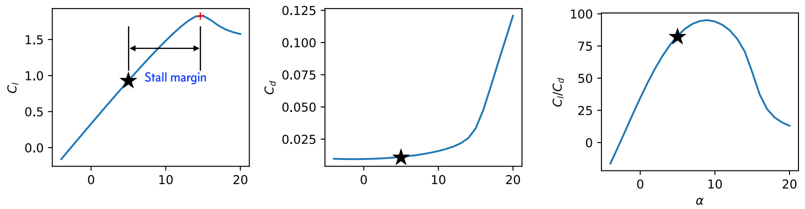
Identify candidate airfoils with $\pm$20% of a baseline airfoil which satisfy the following performance criteria

$\mathrm{Re} = 9\times 10^6$
$C_d < 0.017$
$C_l/C_d > 80$
$\alpha_{\mathrm{stall}} - \alpha > 3°$
$(t/c)_{\max} > 24\%$



Strategy: Train an AI/ML surrogate model for HFM CFD that is **invertible by construction**.

This allows for rapid generation of new shapes for different performance criteria.



Airfoil polars with desired performance

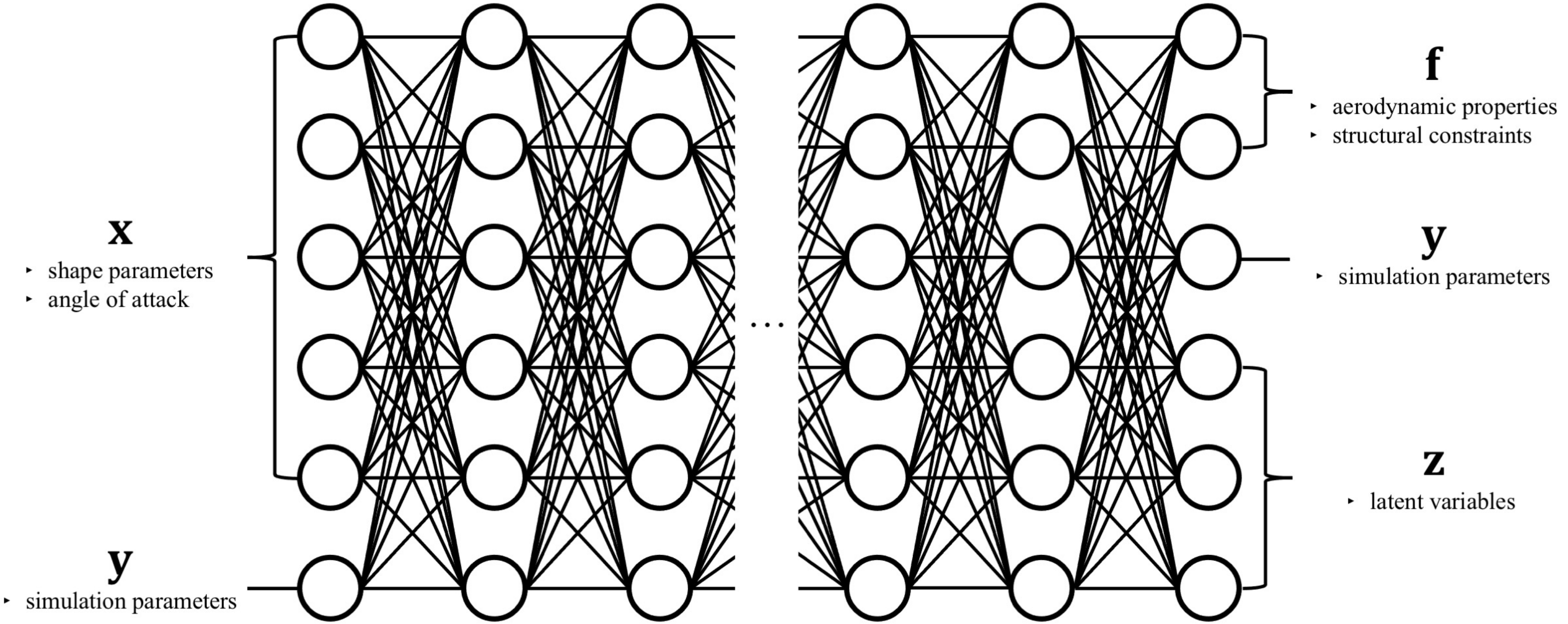
Invertible Neural Network Design

The INN learns a bijection

$$\mathbf{f}_{INN}(\mathbf{x};\boldsymbol{\Theta}) = \begin{bmatrix}\mathbf{f}\\ \mathbf{z}\end{bmatrix}$$

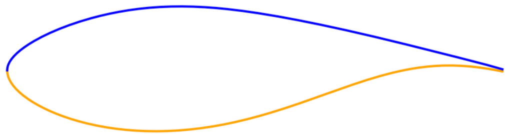
Activations functions in each layer are constructed with closed form inverses

Supervised: $[\mathbf{x},\mathbf{y}] \to \mathbf{f}$
Supervised: $[\mathbf{x},\mathbf{y}] \to \mathbf{y}$
Unsupervised: $[\mathbf{x},\mathbf{y}] \to \mathbf{z}$



Unsupervised: $[\mathbf{f},\mathbf{y},\mathbf{z}] \to \mathbf{x}$
Supervised: $[\mathbf{f},\mathbf{y},\mathbf{z}] \to \mathbf{y}$

Training Data

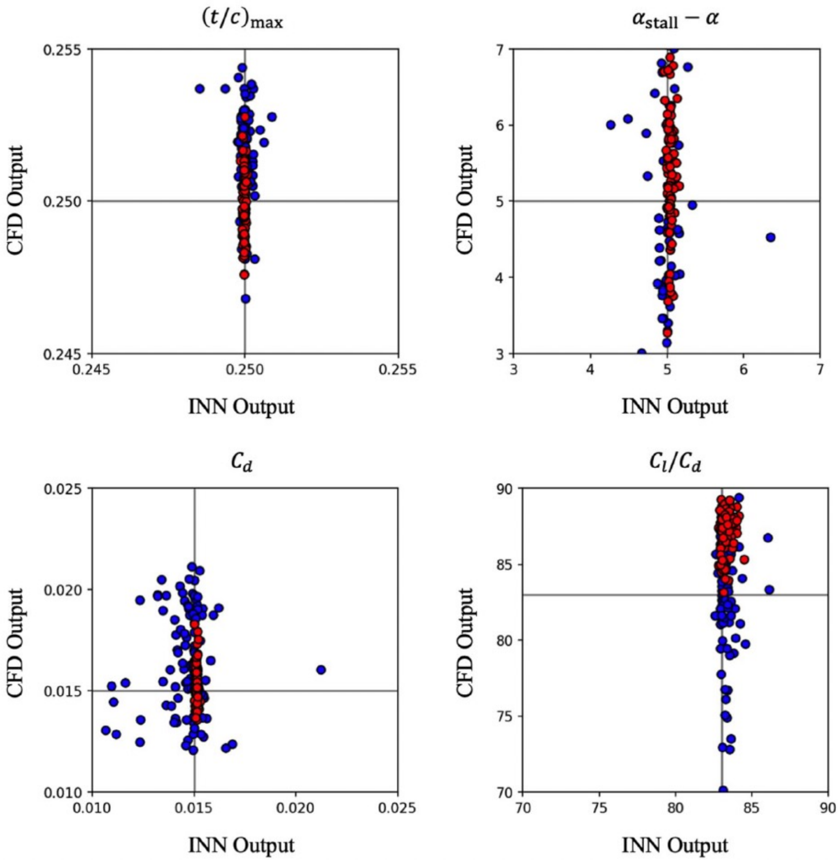


- Airfoil shapes are defined using the Class-Shape Transformation (CST)
  - 20 parameters per airfoil from a Bernstein polynomial expansion
- High fidelity forward model: Hamiltonian CFD solver (HAM2D) from UMD

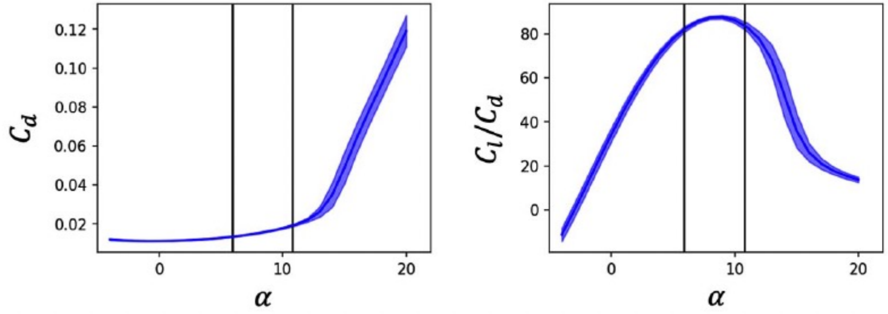
$$\mathbf{x} = \begin{bmatrix} \mathbf{CST}_{\text{upper}} \\ \mathbf{CST}_{lower} \\ \alpha \end{bmatrix}, \quad \mathbf{y} = [\text{Re}], \quad \mathbf{f} = \begin{bmatrix} C_d \\ C_l/C_d \\ \alpha_{\text{stall}} - \alpha \\ (t/c)_{\text{max}} \end{bmatrix}, \quad \text{and} \quad \mathbf{z} = [\text{latent variables}]$$

- Design space defined by $\pm 20\%$ perturbation about a baseline airfoil (DU25)
  - $\text{Re} \in \{3{\times}10^6, 6{\times}10^6, 9{\times}10^6, 12{\times}10^6\}, \alpha \in [-4°, 20°]$
- 801 perturbed shapes w/ sweeps across Re and $\alpha \rightarrow$ 80,100 total CFD runs

2D Airfoil Results



100 unique shapes all satisfying criteria



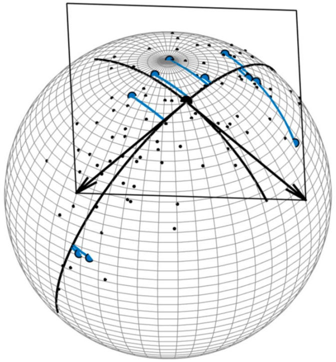
$$err = 100 \times \left| \frac{f_{\mathrm{INN}} - \bar{f}}{\bar{f}} \right|$$

INN Validation Errors		C_d	C_l/C_d
Baseline	Mean	16.1%	4.2%
	Std. Dev.	10.1%	3.7%
Updated Version	Mean	3.1%	6.1%
	Std. Dev.	2.1%	1.5%

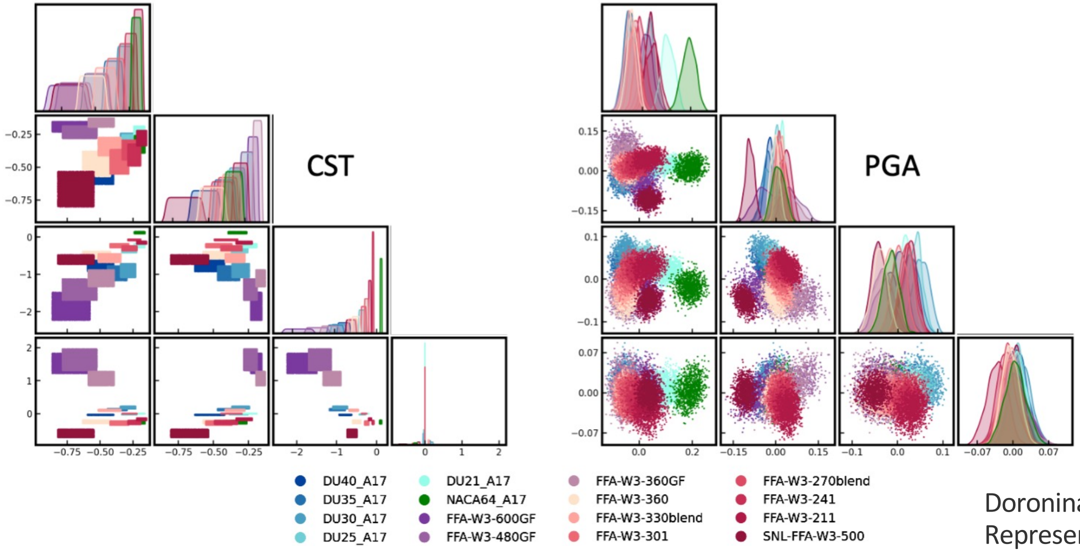
A. Glaws, R. King, G. Vijayakumar, S. Ananthan, *Invertible Neural Networks for Airfoil Design*. AIAA Journal, 2022.

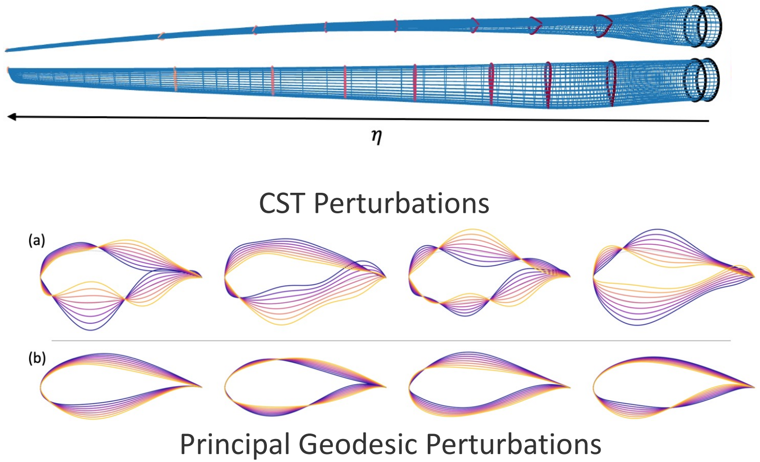
Airfoil Parameterization

- CST parameterization flaws: disjoint design space and unphysical perturbations
- Parameterization with Grassmann manifolds allows shapes to be sampled and smoothly deformed independent of affine transformations or rotations.
- Principal geodesic analysis (PGA) basis r=4 instead of 20 CST parameters



Principal geodesics in Grassmann space



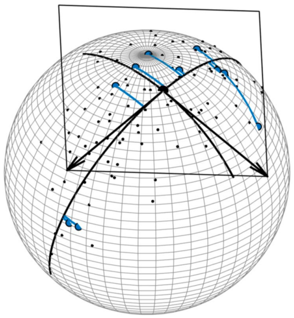


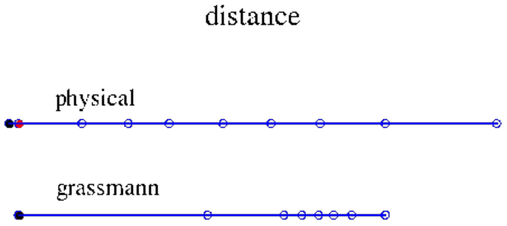
Doronina, Olga A., Zachary J. Grey, and Andrew Glaws. "Grassmannian Shape Representations for Aerodynamic Applications." *arXiv:2201.04649* (2022).

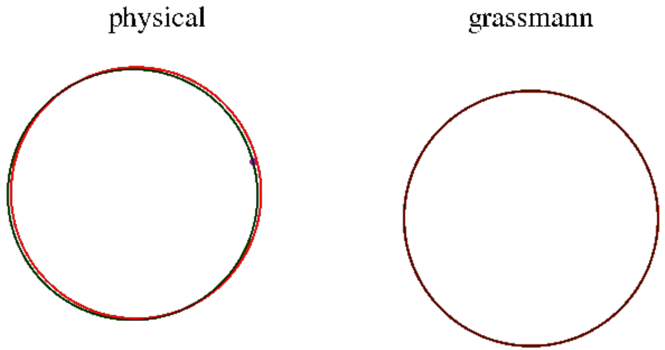
Airfoil Parameterization

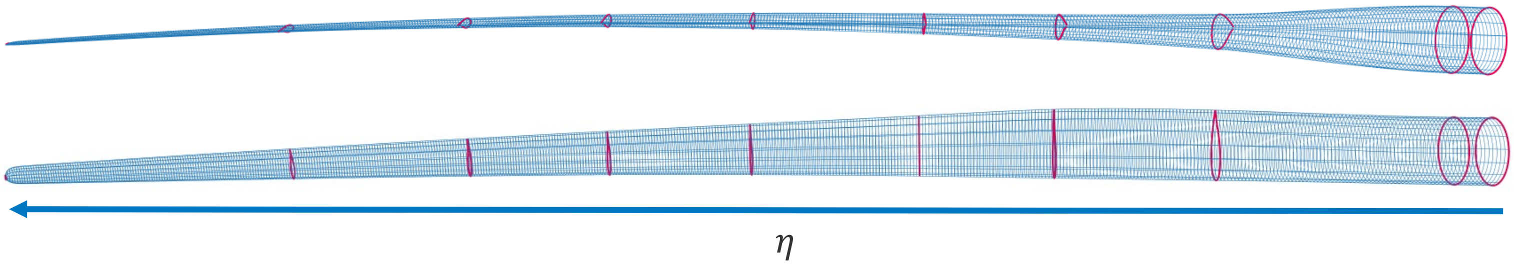
Nominal cross sections at a specific η → Grassmannian interpolation & affine splines → New cross sections in physical space

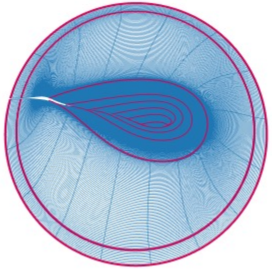
- 3D blades now represented as curves on a Grassmann manifold







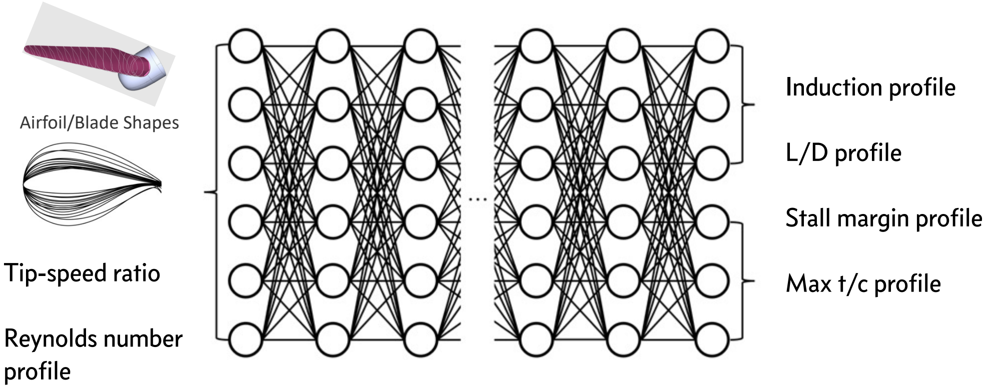




Outer Blade Section Design

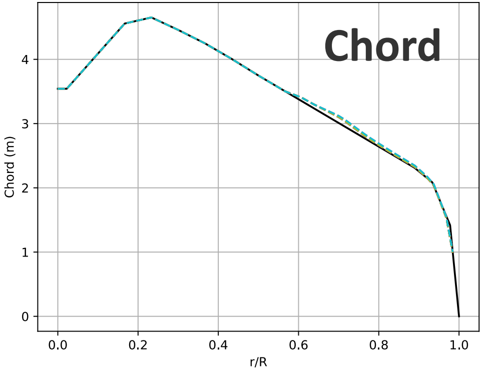
- Designing outboard 60-95% of blade representative of later stages of design
- Goal is to tradeoff some power to increase tip clearance and/or mitigate loads, while also demonstrating INN with full 3D blade representation.
- Control variables: twist and chord profiles, plus outer section airfoil shape, while minimizing thrust and maintaining power.

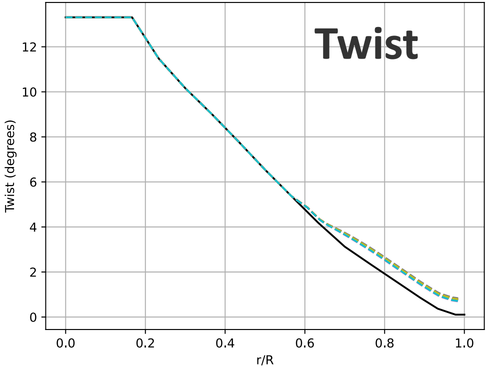
$$
\begin{aligned}
\lambda &= 7.55 \\
Re_{0.75R} &= 8.6 \times 10^6, \\
L/D &> 80, \\
(\alpha_{\mathrm{stall}} - \alpha_{\mathrm{opt}}) &> 5^\circ, \\
(t/c)_{\max} &> 17\%.
\end{aligned}
$$



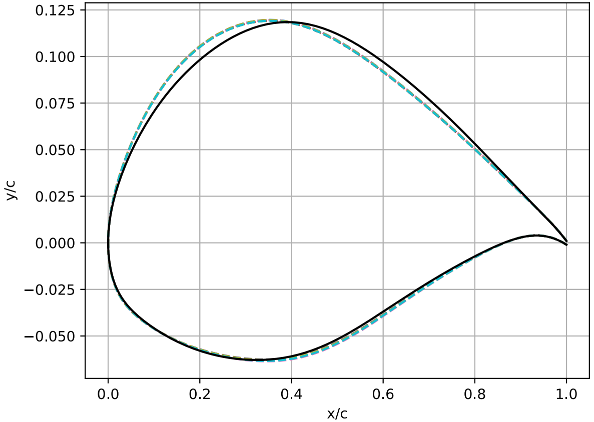
Outer Blade Section Design Results

- All INN-generated shapes and profiles meet design criteria and reduce loads as confirmed by CFD validation of INN output

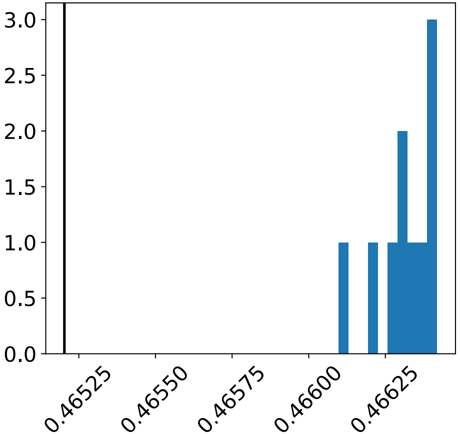




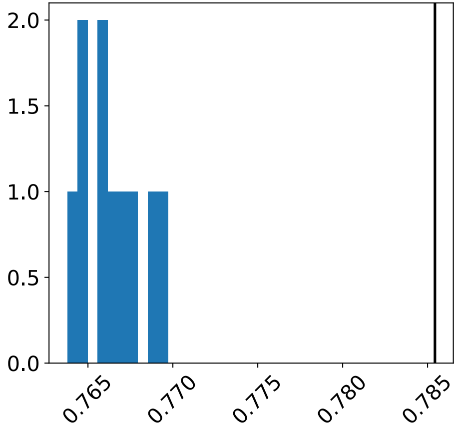
New Shapes



C_P



C_T



INN Outcomes

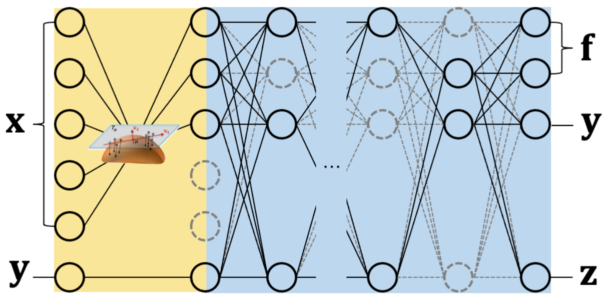
- Dramatic acceleration of airfoil design process, 3D blade design underway

- INN tool integrated into WISDEM suite
  - https://github.com/NREL/INN-interface

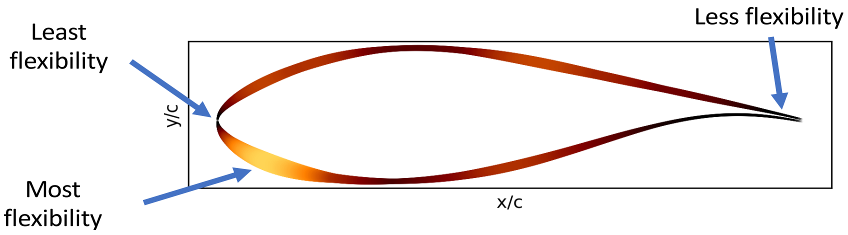
- New conception of 2D and 3D shapes with principal geodesics in Grassmann space

- Differentiability of INN enables gradient-based shape sensitivity analysis that can inform manufacturing tolerances

Example: Airfoil design evaluation
- 20 CFD evaluations
- 2 hours each
- 144000 CPU s
- INN-Design cost: < 1s



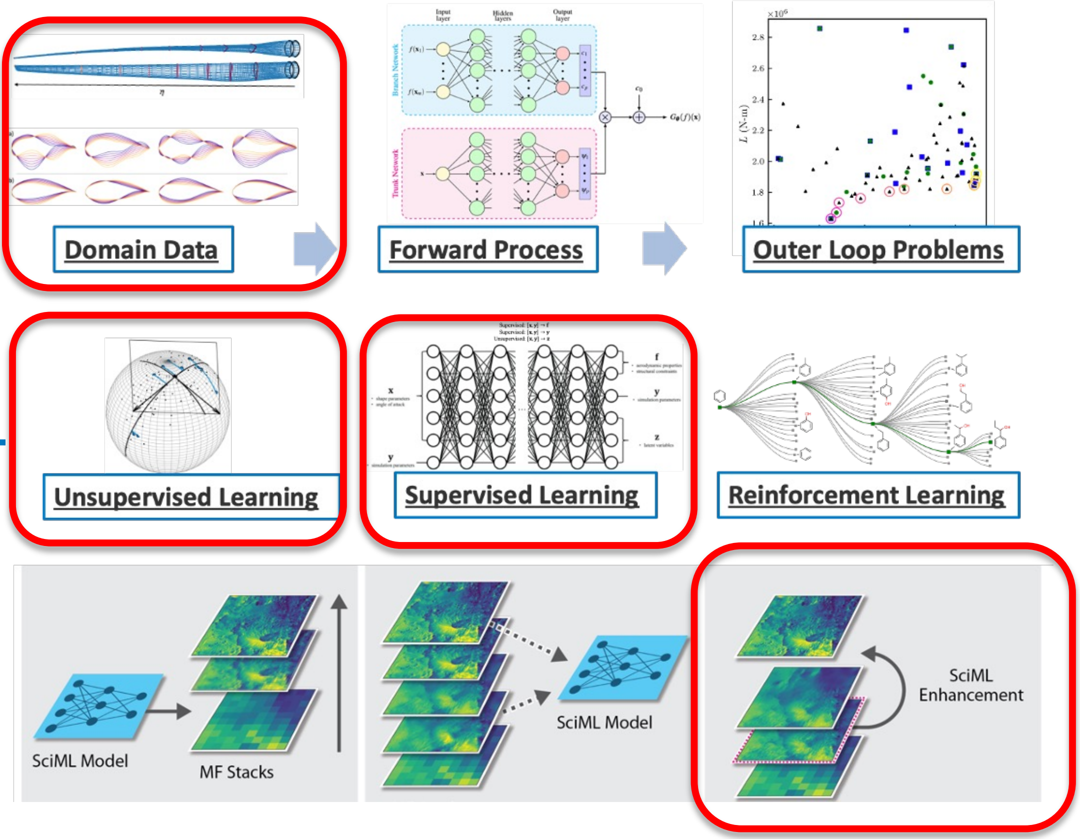
87% dimension reduction of 3D blade parameterization



Example #2

Super Resolution

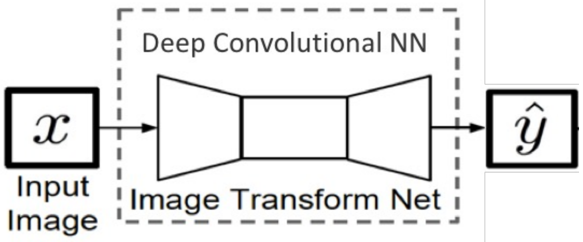
Collaborators: Andrew Glaws, Brandon Benton, Grant Buster, Malik Hassanaly, Julie Lundquist, Dave Rosencrans, Karen Stengel, and Dylan Hettinger

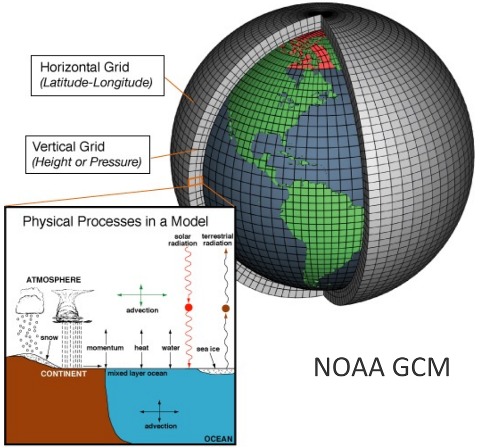


Climate Downscaling Challenge

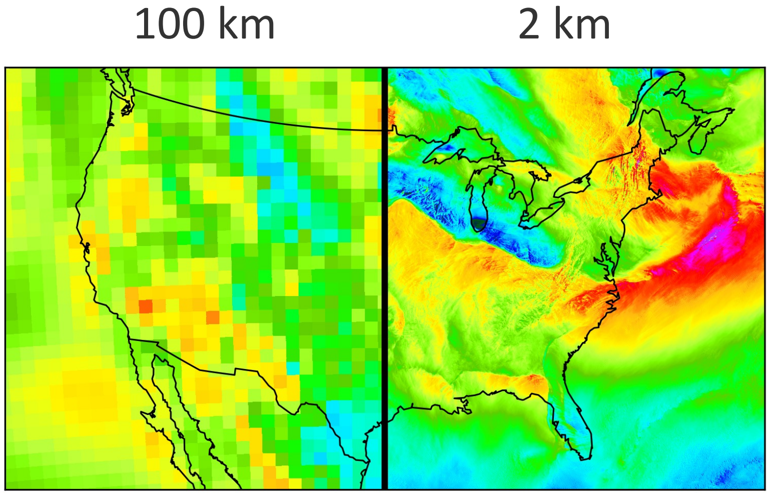
How will future climate scenarios impact the development and operation of renewable energy?

- Global climate models (GCM) use a resolution of ~1 deg. (~100 km).
- Wind and solar resource assessments require resolution of ~2 km.
- Can AI/ML enhance the fidelity of this data?





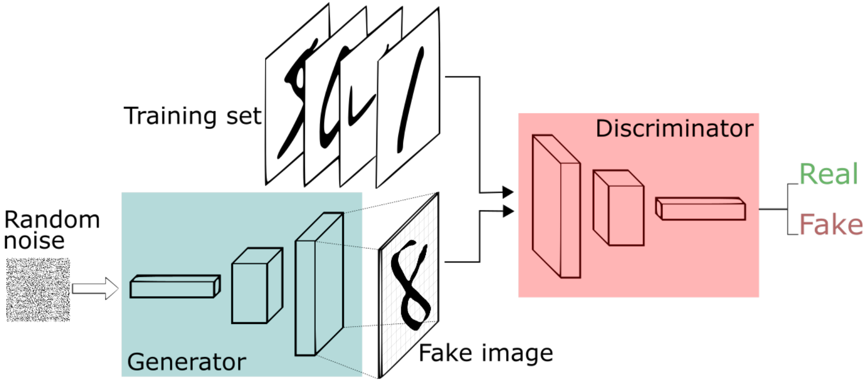
NOAA GCM



Super resolution of climate data

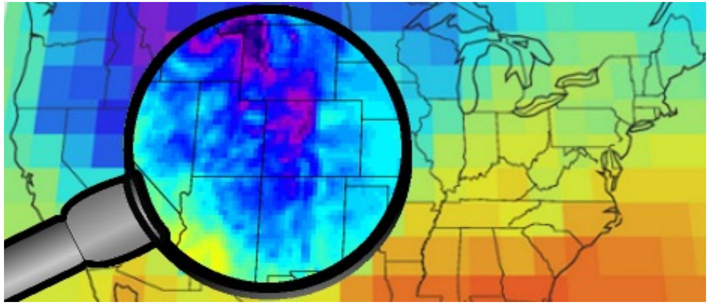
Ledig et al. 2017

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



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

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



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

Using SR to Downscale GCM Data

HFM Training data: NREL's Wind Integration National Database Toolkit (WTK) based on WRF

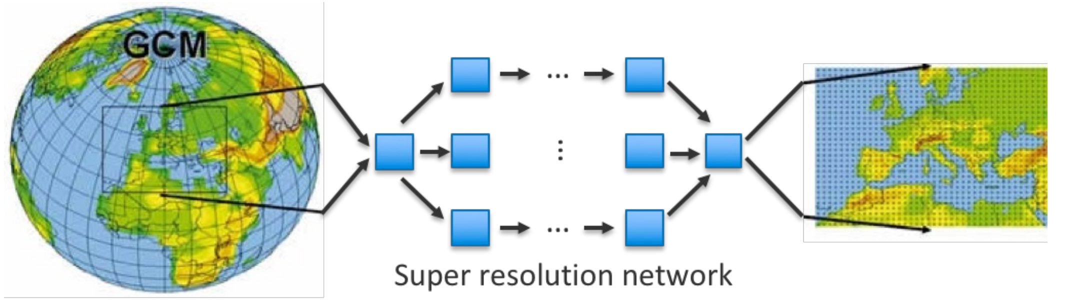
Application deployment: NCAR's Community Climate System Model (CCSM) used in CMIP5 IPCC studies

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

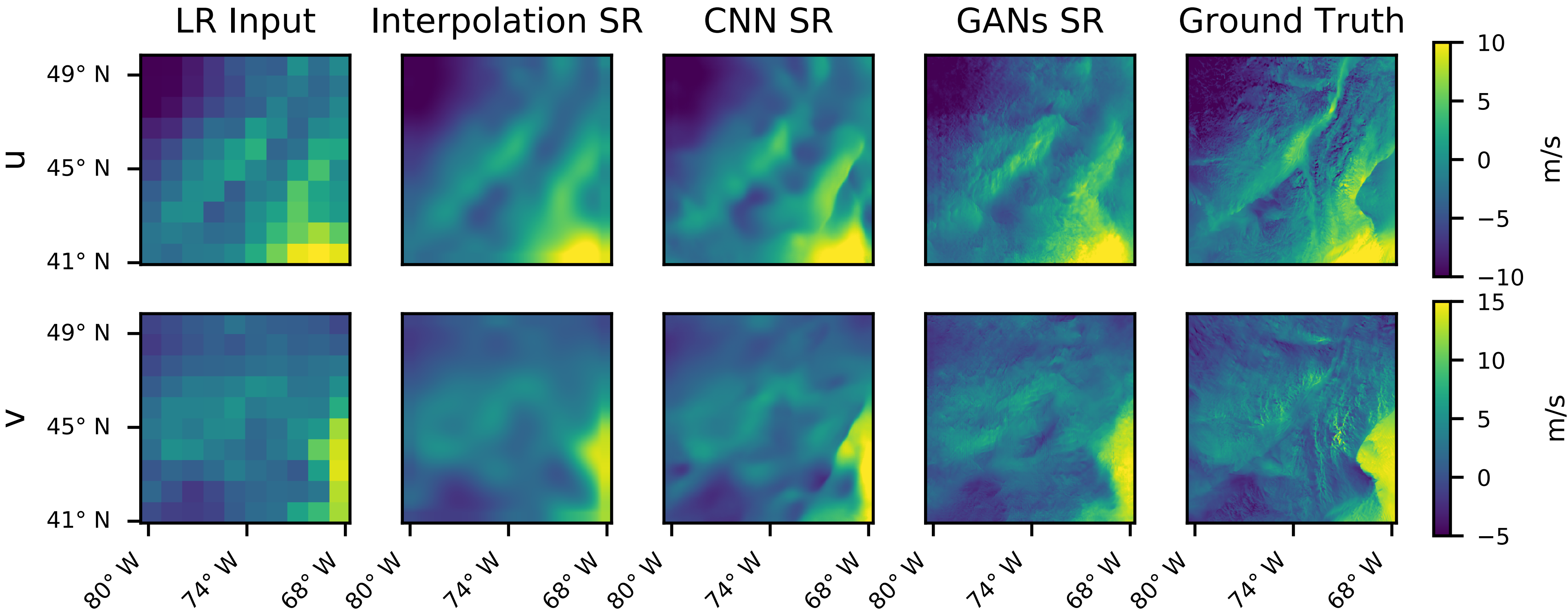
1. Train super resolution networks on coarsened WTK/NSRDB data.

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



Quantifying Improvements in Generated Fields

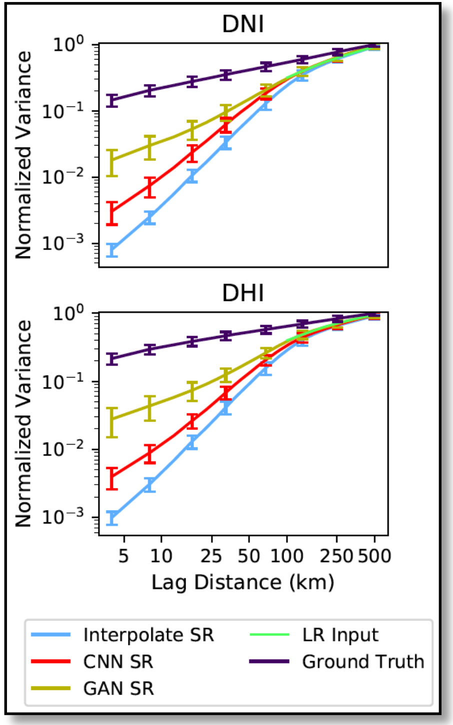
- Adversarial training produces quantifiable improvements in physical quality
  - Correct turbulent statistics
  - DNI & DHI semivariogram improved
- Perception/distortion tradeoff
  - Adversarial training increases MSE

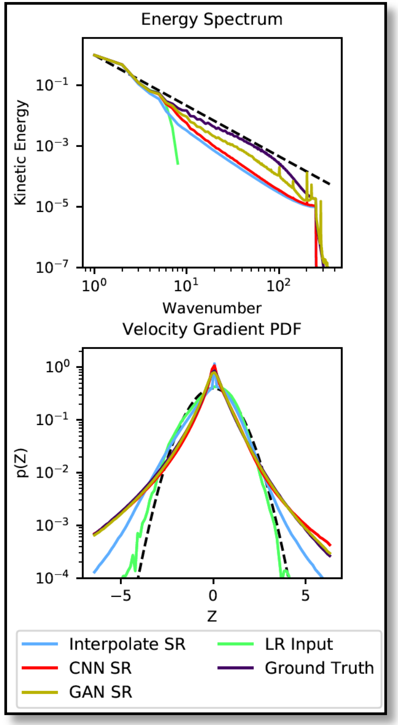
$$\mathcal{L}_G(\mathbf{x}, \mathbf{y}) \;=\; \mathcal{L}_{content}(\mathbf{x}, \mathbf{y}) + \alpha\, \mathcal{L}_{adversarial}(\mathbf{x}, \mathbf{y})$$

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

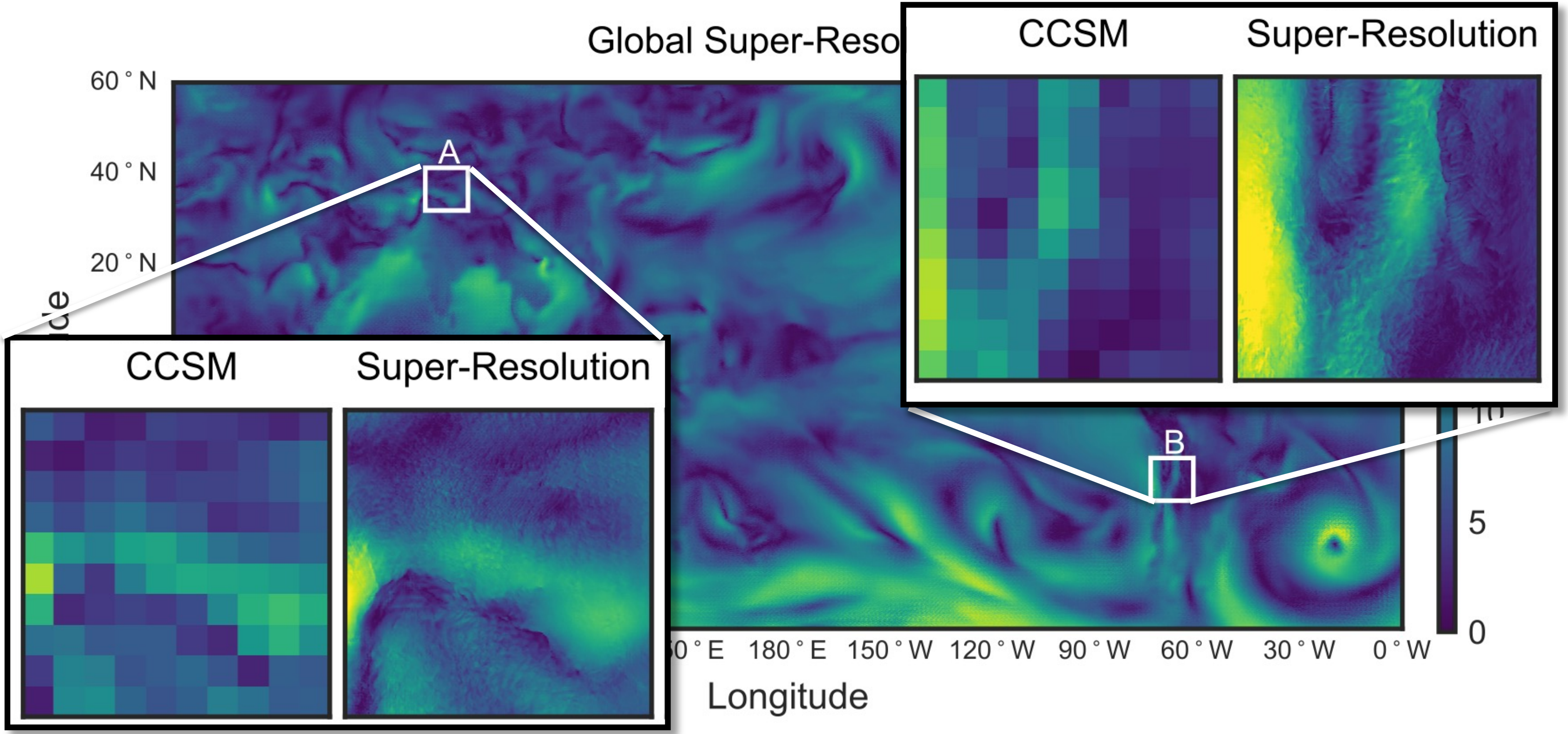
Quantity	Bicubic Interpolation	Pretraining	Adversarial
DNI	0.155	0.078	0.086
DHI	0.135	0.073	0.085





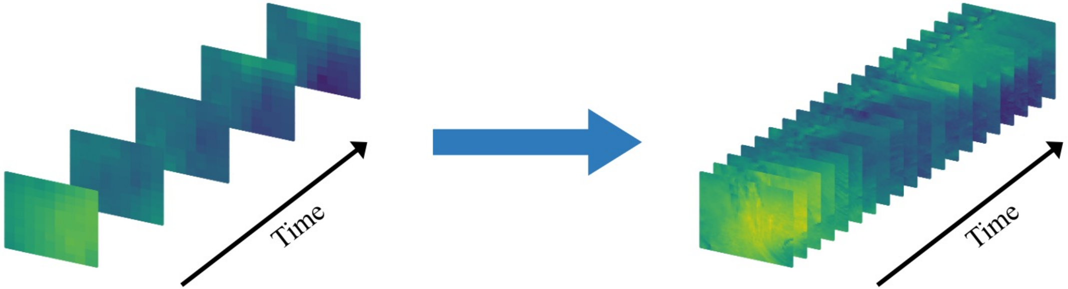
K.Stengel, A. Glaws, D. Hettinger, and R. King. PNAS, 2020

Evaluating on Global Data



Spatiotemporal Super Resolution

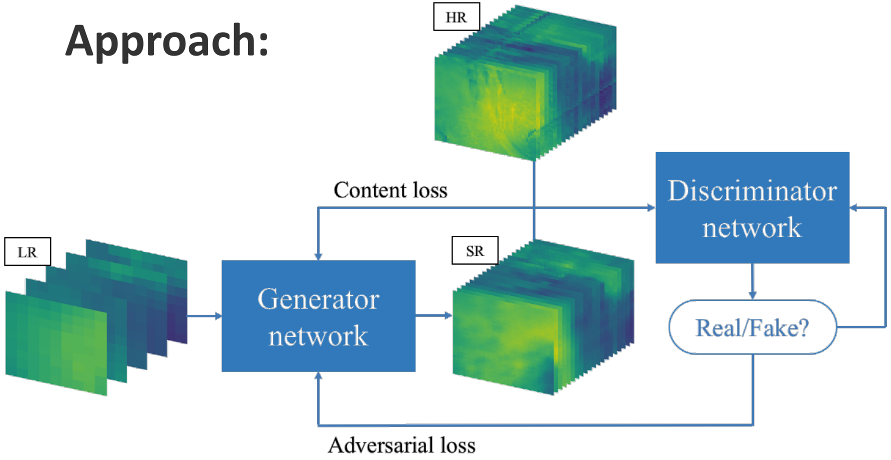
Goal: extend methods for enhancing spatial resolution of climate data to temporal domain



Daily -> hourly or

hourly -> 5 minute

Approach:



Challenges:

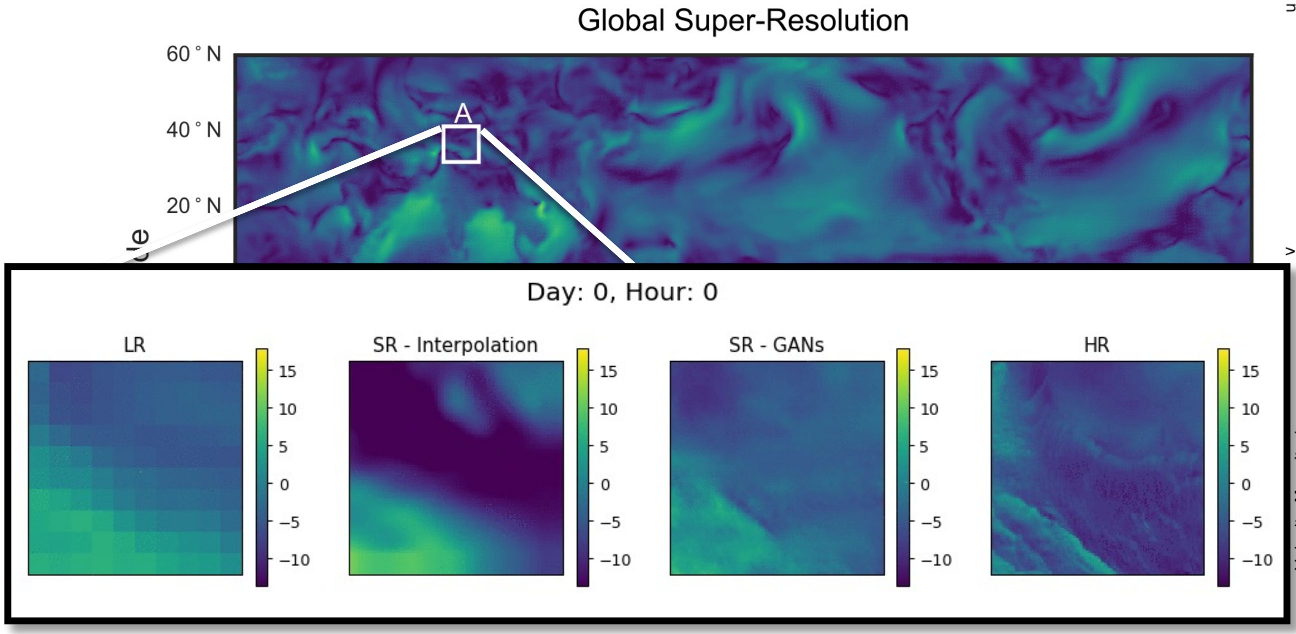
- Significant increase in enhanced details

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

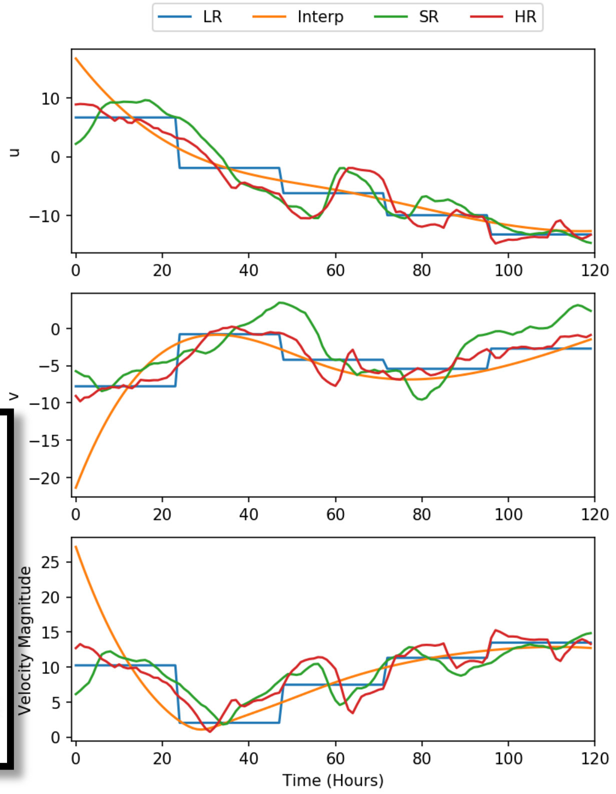
- Memory constraints require smaller batch sizes
- Single spatio-temporal discriminator

Spatiotemporal SRGANS

Simultaneous 24x temporal and 10x spatial resolution enhancement



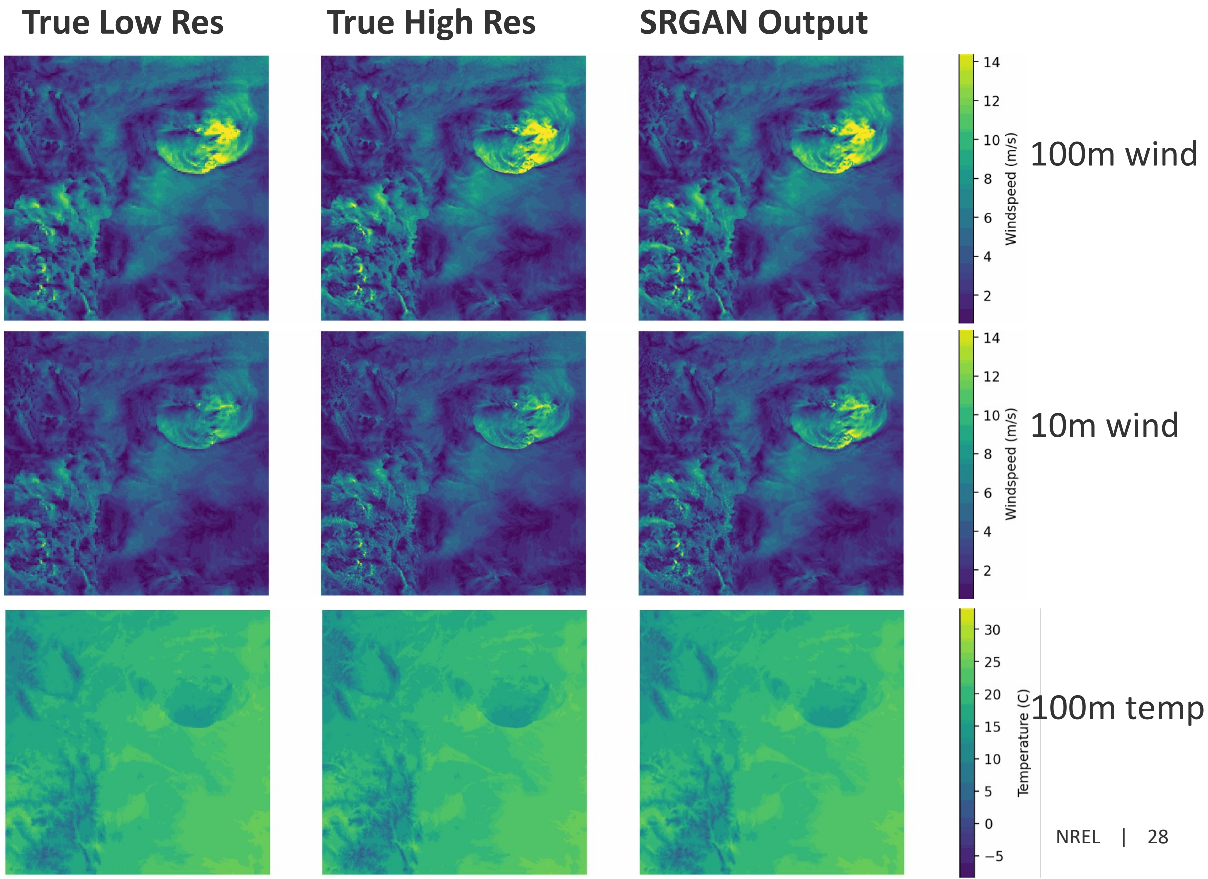
GANs learns advection which leads to more accurate wind ramp rates



Spatiotemporal SRGANS

- Latest extensions include multiple hub heights and multiple atmospheric variables, plus inclusion of terrain.

- Example: 4x temporal and 3x spatial enhancement of 1500km x 1500km region replacing 1 layer of WRF nested grid



Super Resolution Outcomes

- Open source spatio-temporal super resolution tool: https://github.com/NREL/sup3r
- Applicable to arbitrary sized input domains (local/regional/global), and up to 50x spatial and/or 24x temporal enhancement
- Can enhance multiple atmospheric variables simultaneously and at different heights for operational forecasting or long term planning applications
- Super resolution capability is being used in many other ongoing climate scenario and forecasting studies at NREL, e.g. hurricanes, flood risk, sea level rise, land use changes, etc.

Thanks!

ryan.king@nrel.gov