WiSoSuper:

Benchmarking Super-Resolution of Wind and Solar Data

Rupa Kurinchi-Vendhan
California Institute of Technology
2021 NeurIPS Workshop on Tackling Climate Change with AI

Lucien Werner, Steven Low
(Netlab)
California Institute
of Technology

Ritwik Gupta
Defense Innovation Unit
University of
California, Berkeley

Björn Lütjens, Dava Newman
(Human Systems Laboratory)
Massachusetts Institute
of Technology

The

U.S. Energy Information Administration (EIA)

predicts that renewable energy, predominantly

wind and solar

power, will contribute

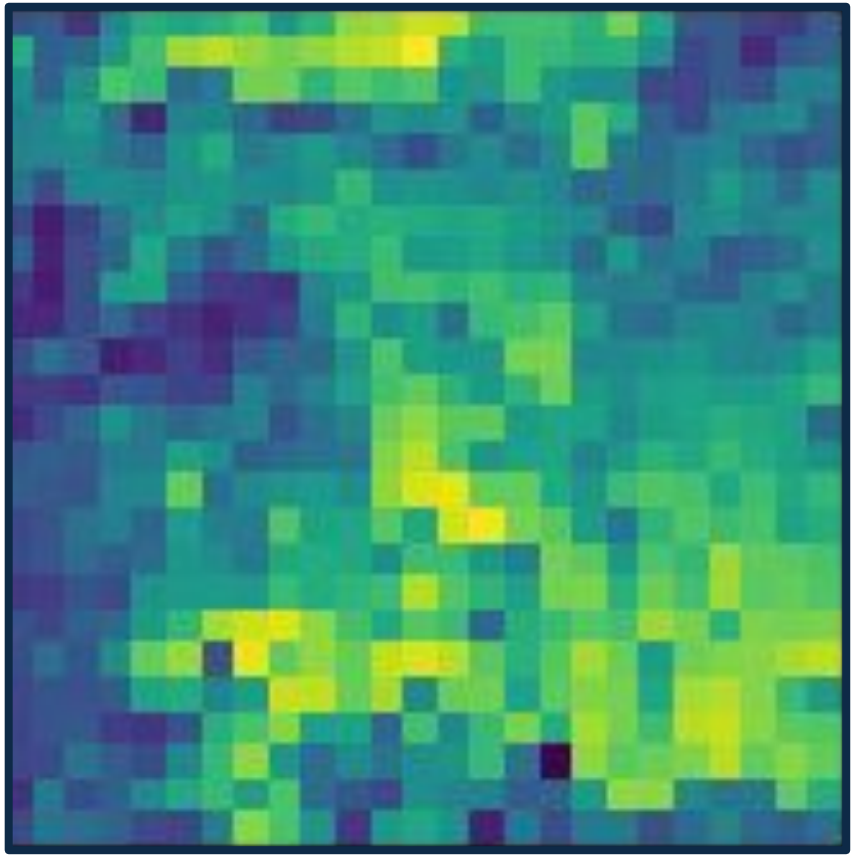
42%

of the country's electricity generation by 2050.

(*Annual Energy Outlook 2021*. U.S. Energy Information Administration, 2021.)

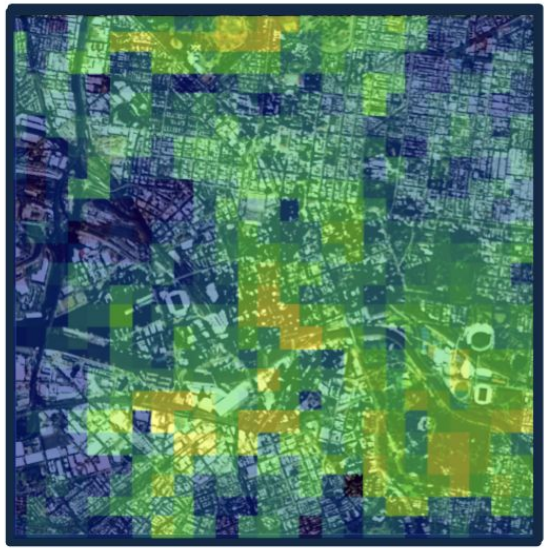
NWPs

This is wind speed data on the **10-km** scale.

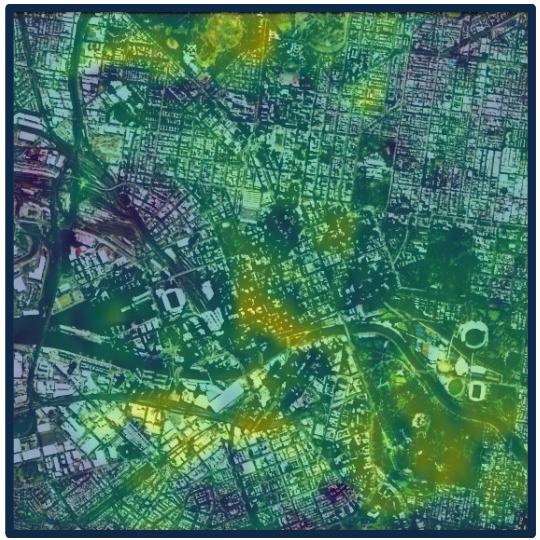


A. Clifton, B.-M. Hodge, C. Draxl, J. Badger, and A. Habte, “Wind and solar resource data sets,” *Wiley Interdisciplinary Reviews: Energy and Environment*, vol. 7, no. 2, p. 276, 2018.

We want to find an accurate and realistic **mapping** between **low-resolution** and **high-resolution** wind and solar data.

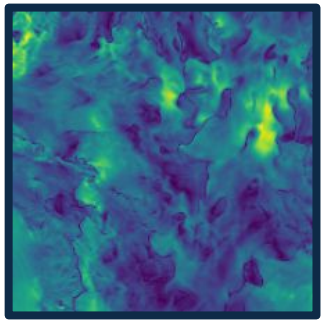


LR Input



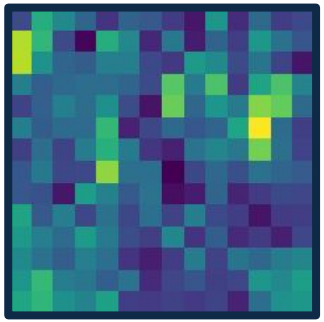
HR Output

The problem of super-resolution is **ill-posed.**



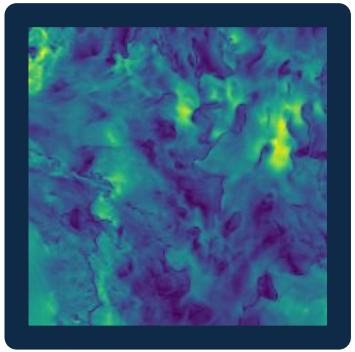
HR Ground Truth

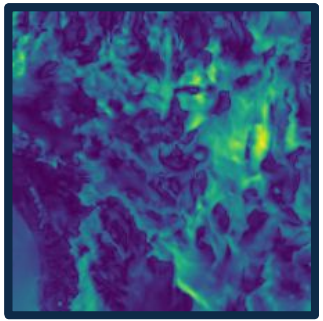
Downsample



LR Input

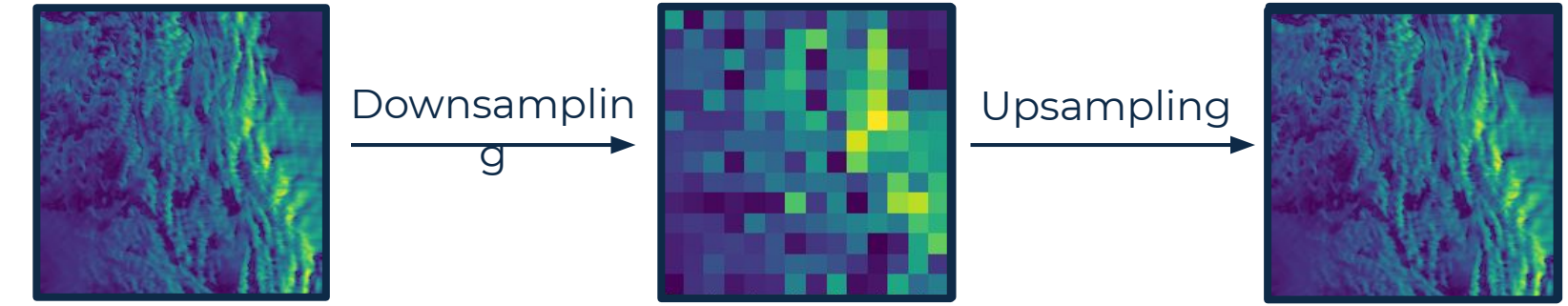
Upsampling





SR Output

Machine learning offers a **cost effective** and **accurate** solution.



How do super-resolution models perform on wind and solar data with respect to accuracy and spectral similarity to the ground truth data?

Contributions

We contribute:

- a benchmark of super-resolution models for wind and solar data;
- a novel application of convolutional neural network (CNN)- and generative adversarial network (GAN)-based SR techniques to climate data;
- and publicly-available ML-ready wind and solar datasets.

Models we Introduce

SOTA

PhIREGAN

Stengel et al. in 2020

ESRGAN

Weng et al. in 2018

EDSR

Lim et al. in 201.

SR CNN

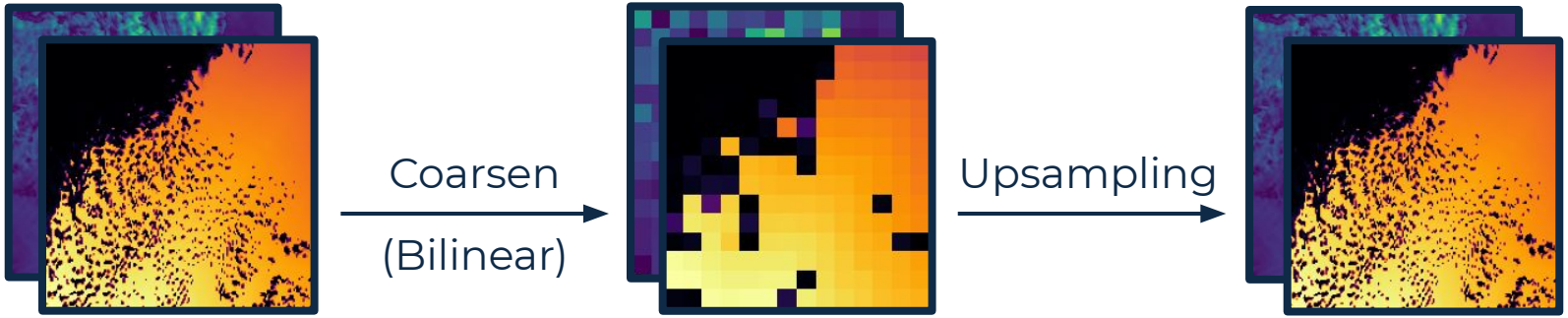
Dong et al. in 2015

Baseline

Bicubic Interpolation

Approach

Train on WIND Toolkit and NSRDB data for 2007-2013.

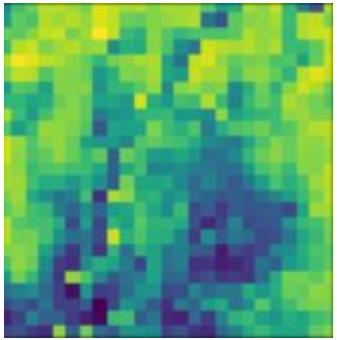


Test 5x upsampling on WIND Toolkit and NSRDB data for 2014 and 2014-2018, respectively.

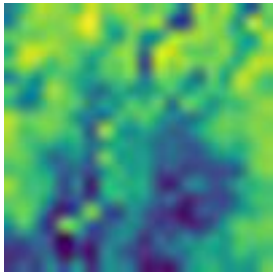
Sample Wind Output

SR Output for Northerly Wind Component (SSIM/MSE).

LR Input

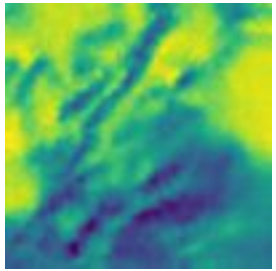


Bicubic



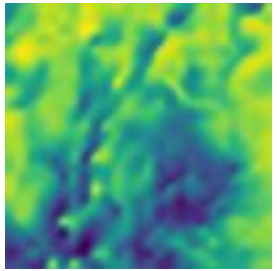
0.143/0.0032

SR CNN



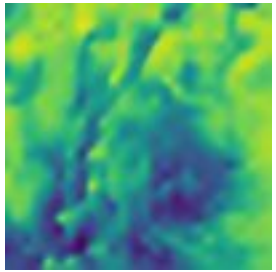
0.542/0.0010

ESRGAN



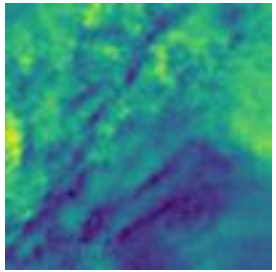
0.497/0.0015

EDSR



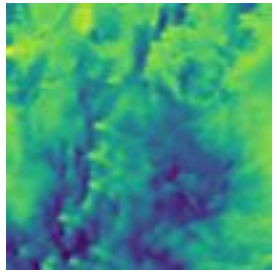
0.766/0.0004

PhIREGAN

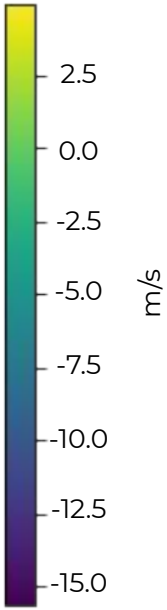


0.447/0.0008

Ground Truth



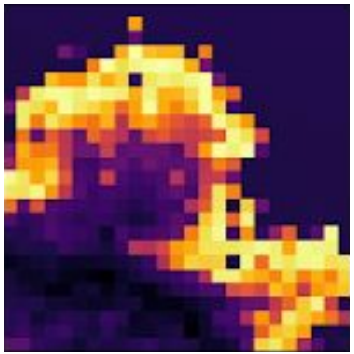
N/A



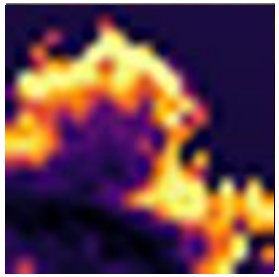
Sample Solar Output

SR Output for Direct Normal Irradiance (SSIM/MSE).

LR Input

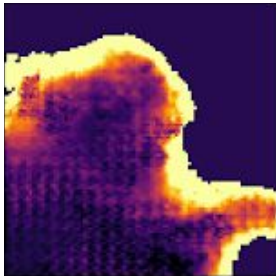


Bicubic



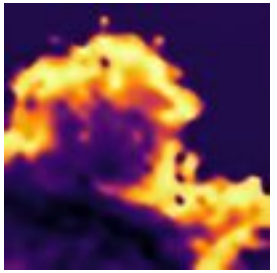
0.466/0.037

SR CNN



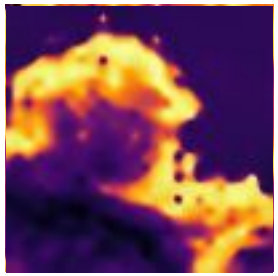
0.464/0.030

ESRGAN



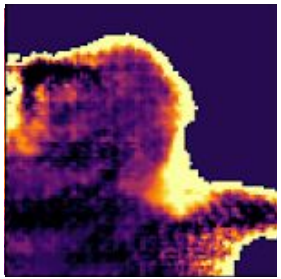
0.678/0.002

EDSR



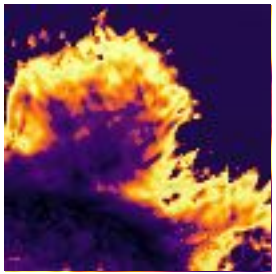
0.543/0.003

PhIREGAN

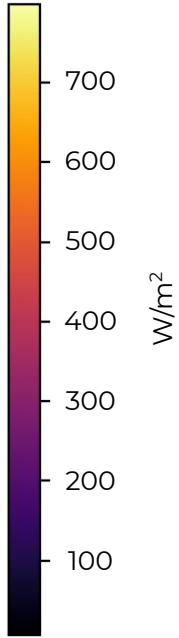


0.441/0.041

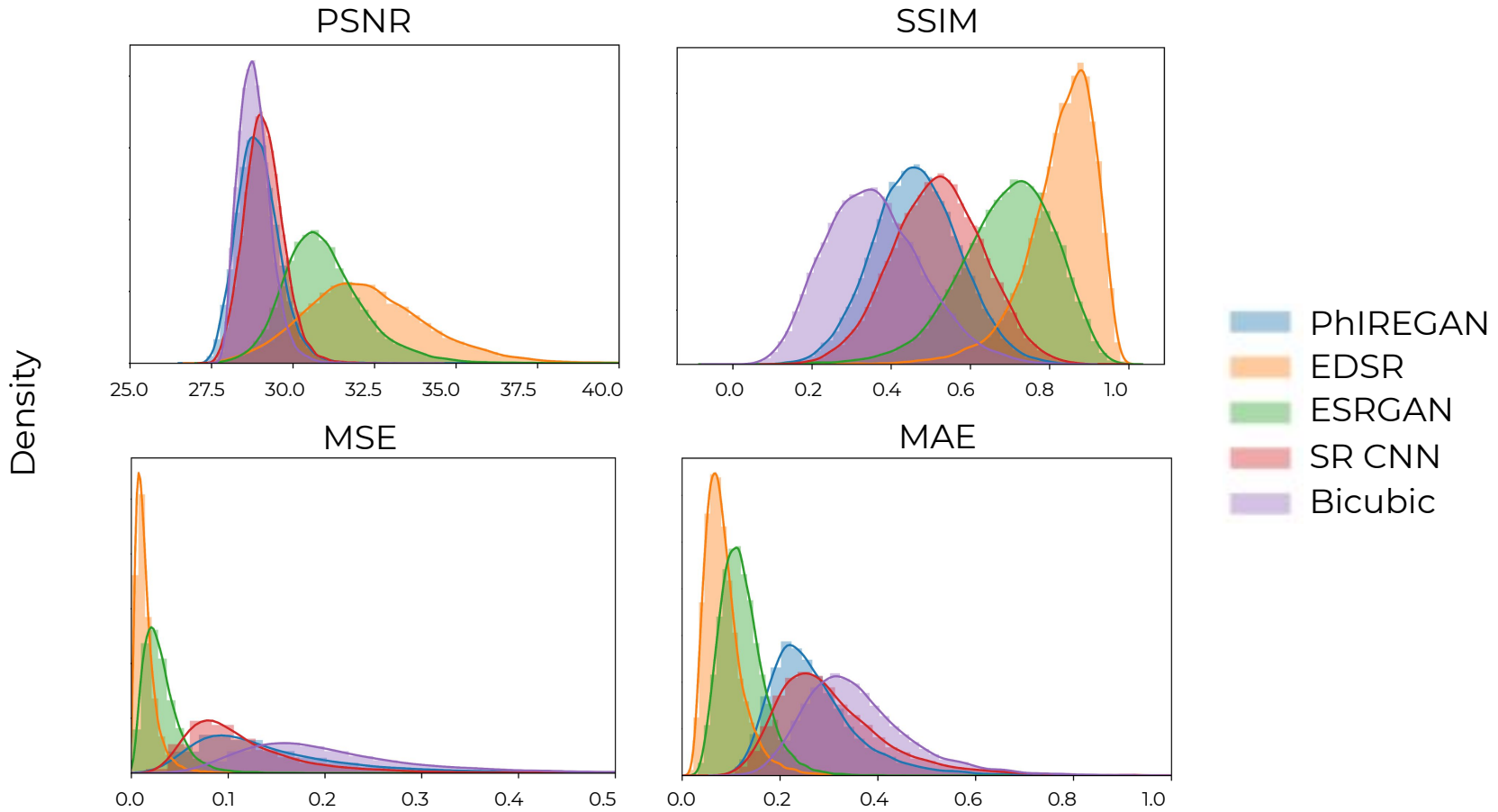
Ground Truth



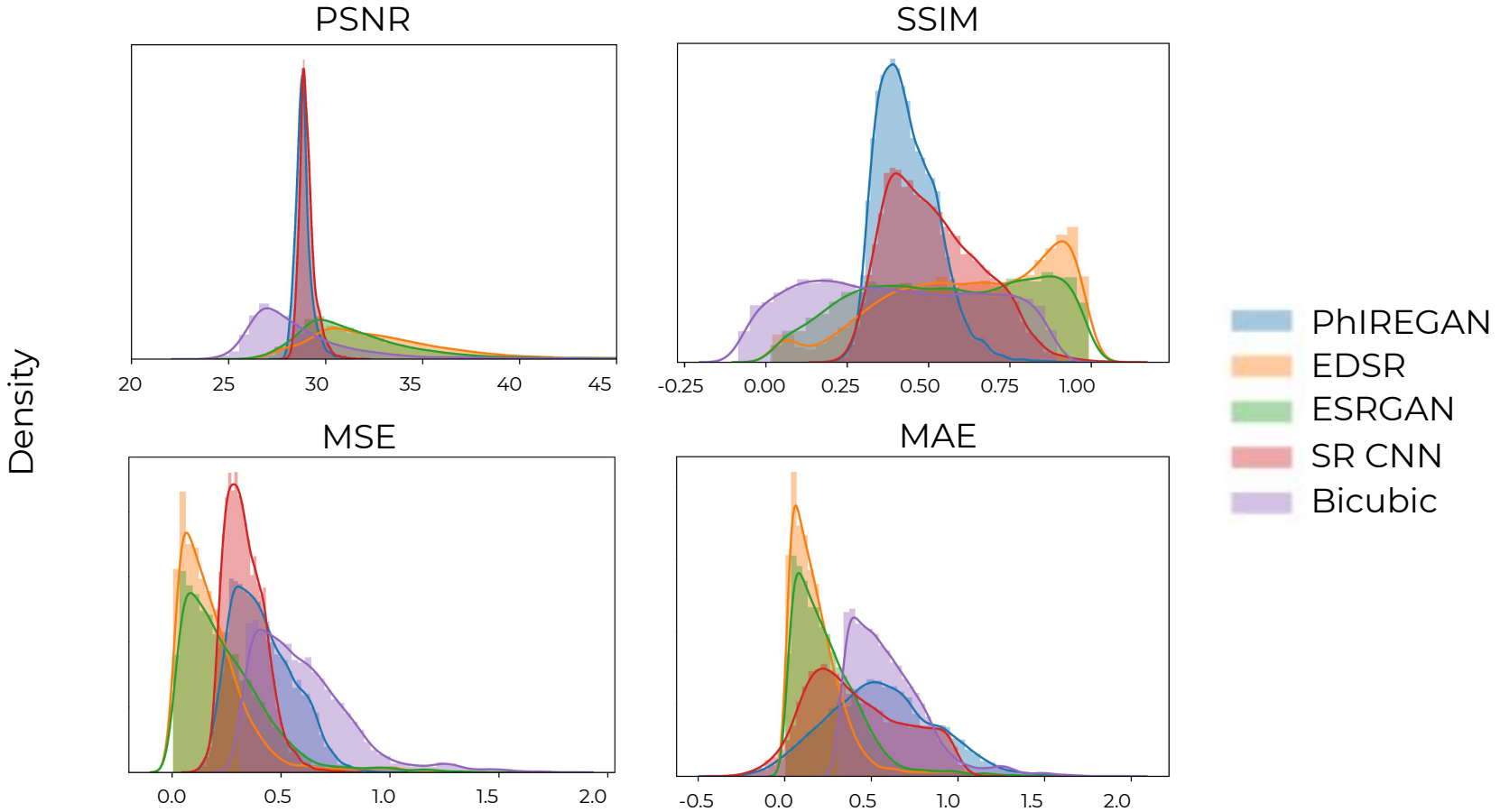
N/A



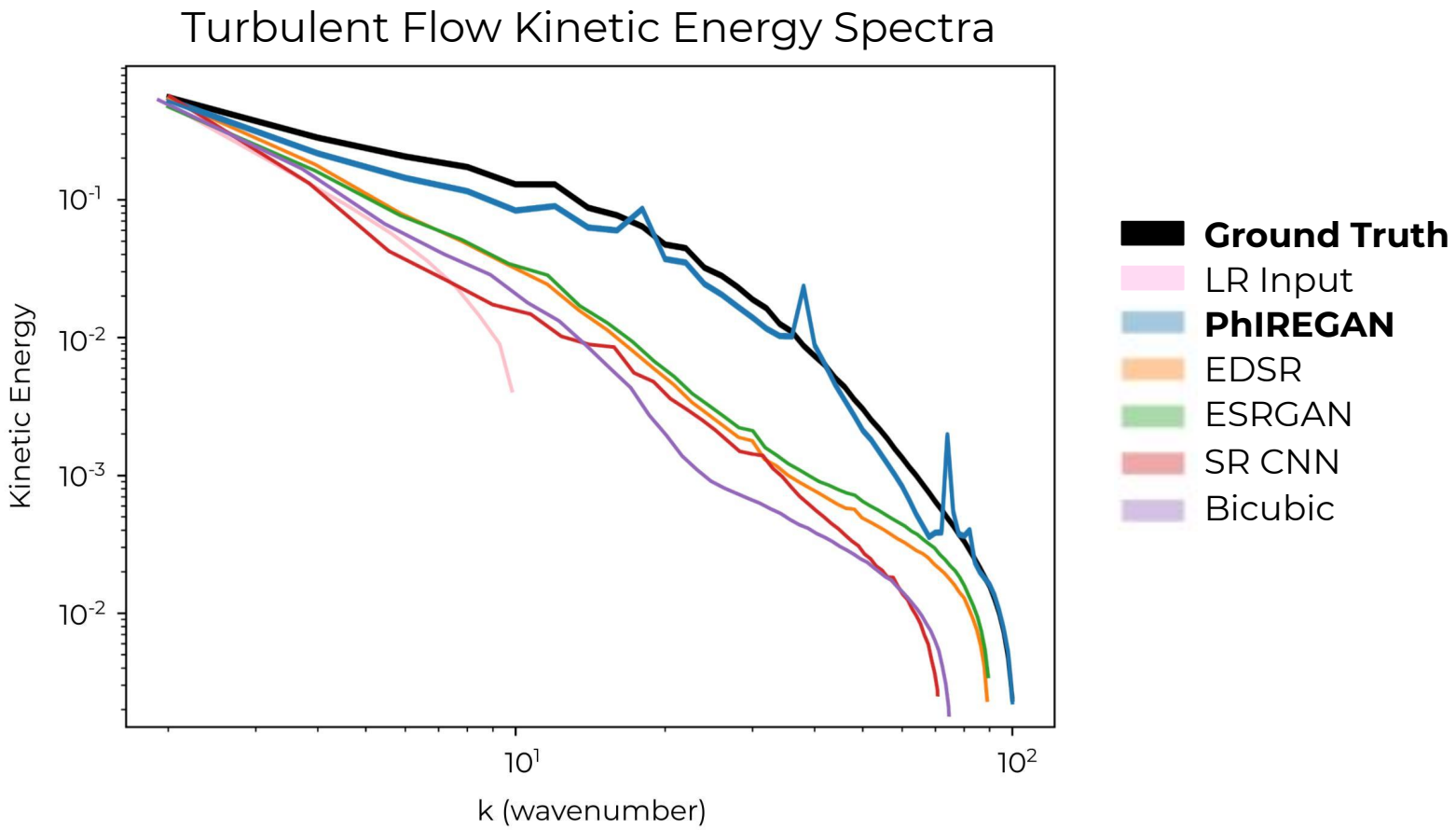
Accuracy of Wind Output



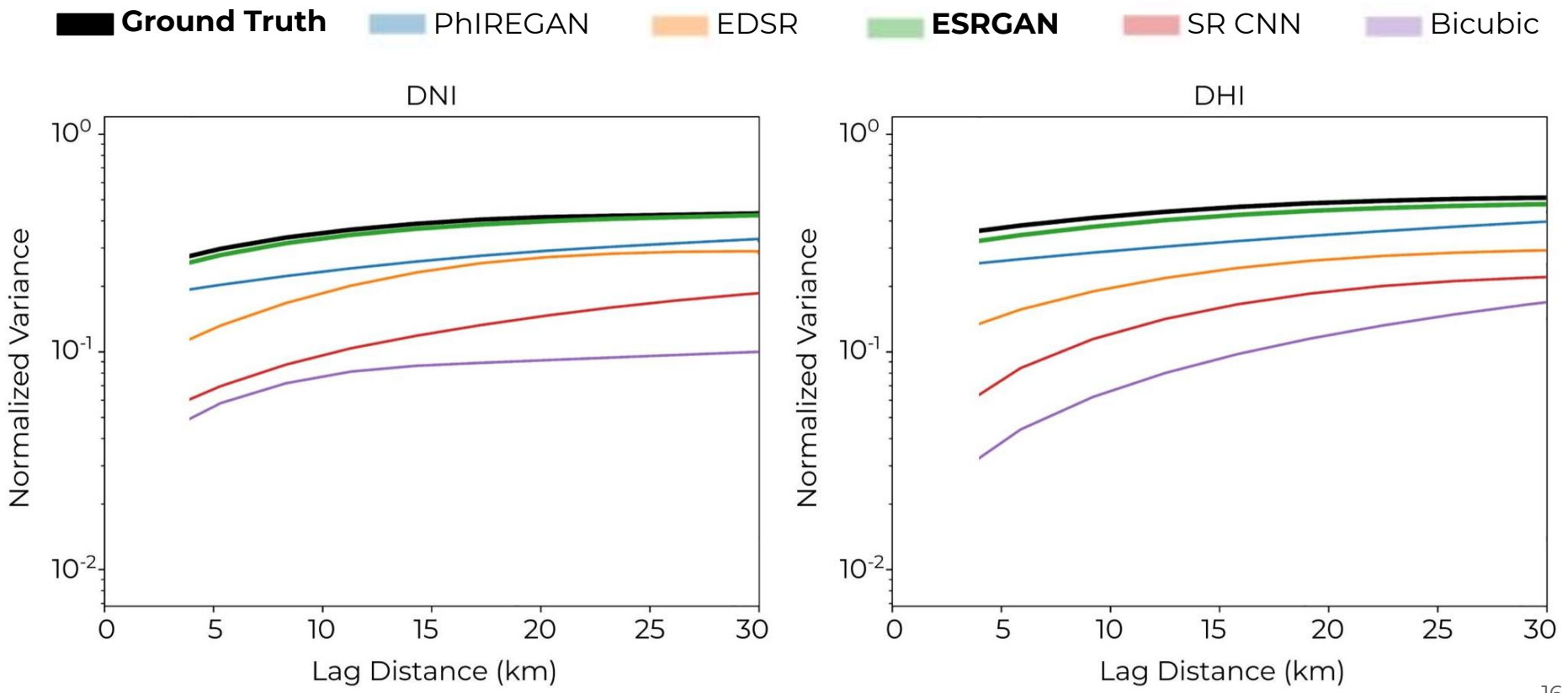
Accuracy of Solar Output



Physical Fidelity of Wind Output



Physical Fidelity of Solar Output



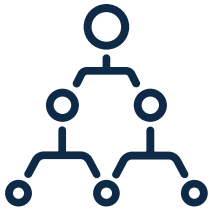
Results

In this work, we show:

1. the perception-distortion tradeoff holds for climate data;

2. and GAN-based models have significant applications in climate scenarios.

Future Works



Include Probabilistic & Physics-Based Models

variational autoencoders, normalizing flows, diffusion-based models, and other models which account for wind flow and irradiance

Test Generalization

verify if results hold when run on datasets with different spatial and temporal characteristics

Thank you!

R. Kurinchi-Vendhan, B. Lütjens, R. Gupta, L. Werner, and D. Newman, “WiSoSuper: Benchmarking Super-Resolution Methods on Wind and Solar Data”, arXiv [cs.CV]. 2021.

rkurinch@caltech.edu @RupaVendhan rupakurinchivendhan