NeurIPS 2020: Tackling Climate Change with Machine Learning

Investigating two super-resolution methods for downscaling precipitation: ESRGAN and CAR

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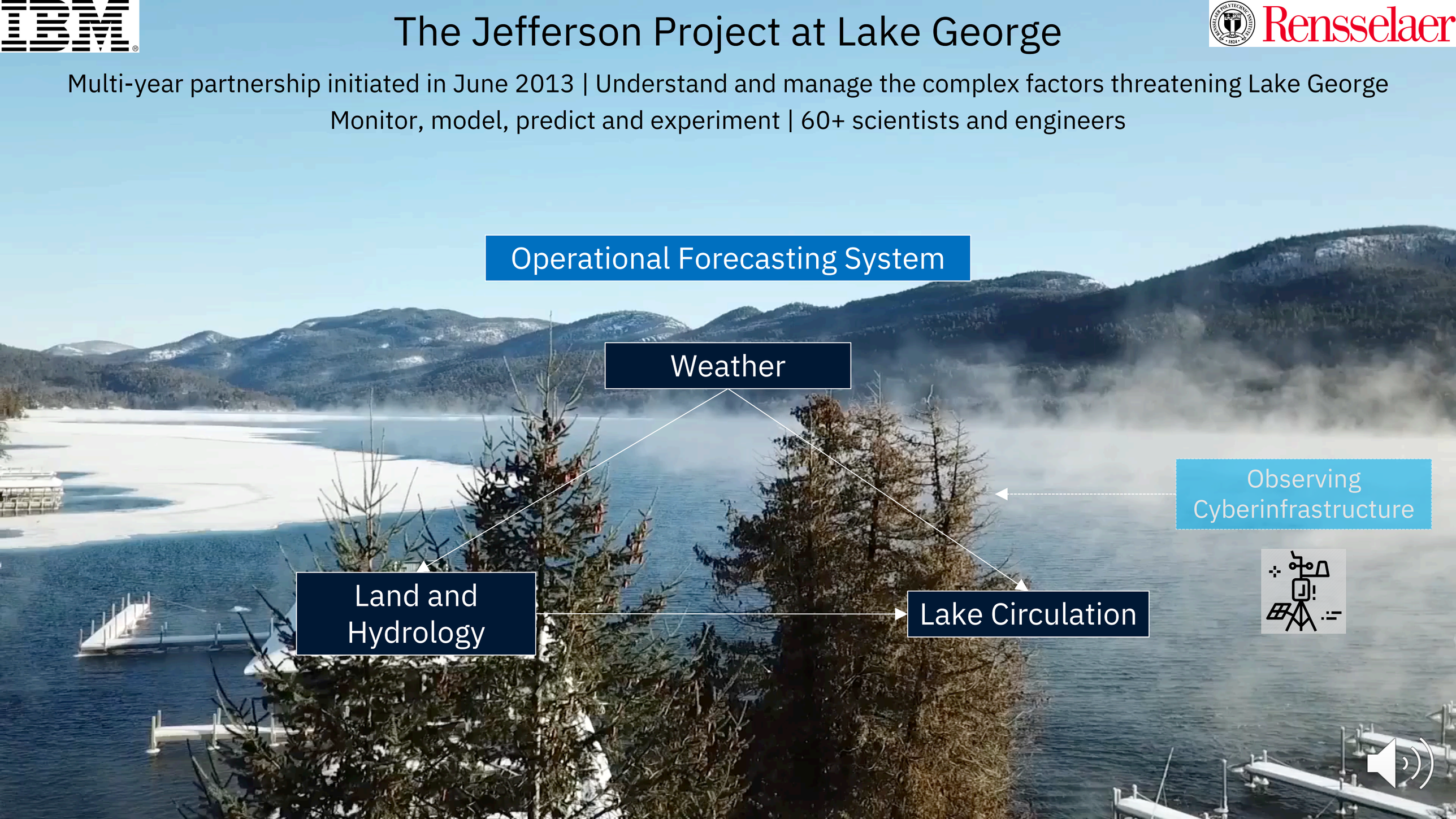
The Jefferson Project at Lake George

Multi-year partnership initiated in June 2013 | Understand and manage the complex factors threatening Lake George
Monitor, model, predict and experiment | 60+ scientists and engineers



manuscript submitted to *Water Resources Research*

The influence of weather forecast resolution on the circulation of Lake George, NY.

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Key Points:

- Higher resolution weather forecast lead to an increase of accuracy in surface water temperature and thermocline depth.
- Conventional weather forecast products lead to loss in accuracy of simulated water temperature for Lake George, NY.
- Improvements in simulated water temperature are linked to a better representation of land use index in the weather model.
- A mismatch of resolution in the weather forecast leads to an underestimation of thermocline and downwelling depths.
- A mismatch of resolution in the weather forecast leads to an overestimation of hypolimnetic volume by 15%.

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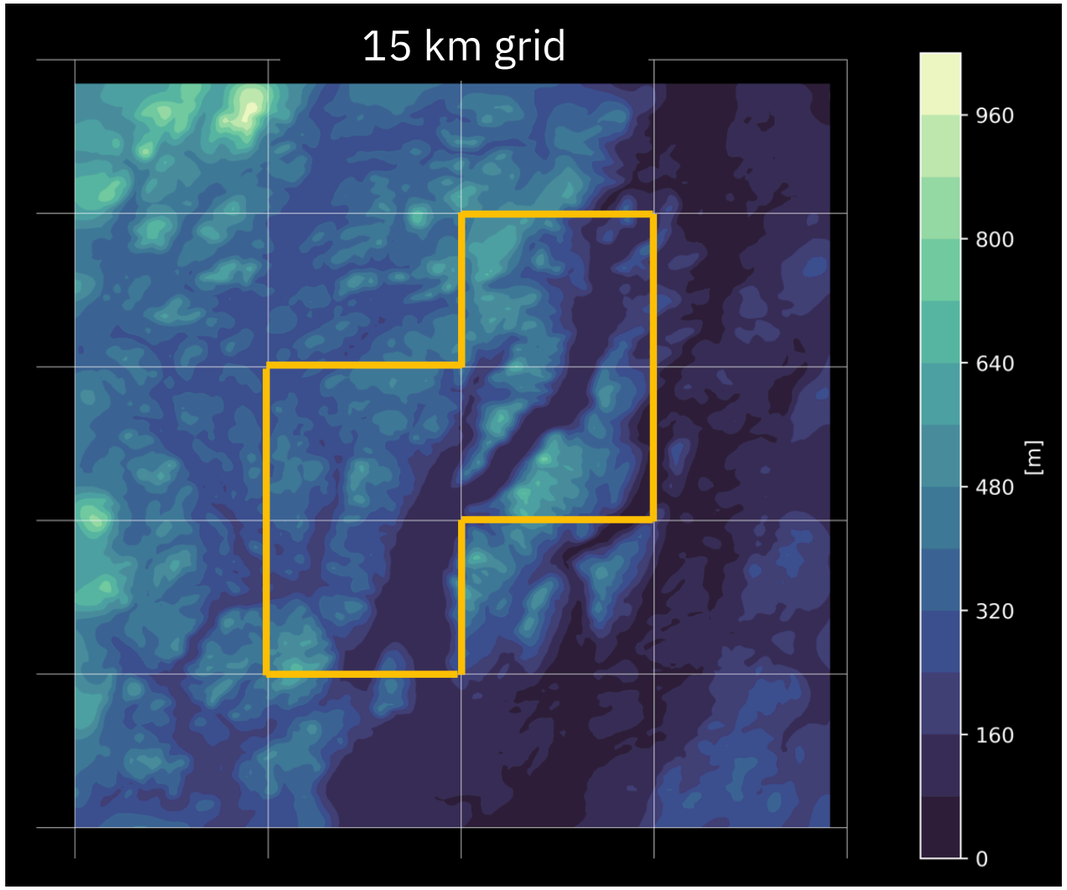
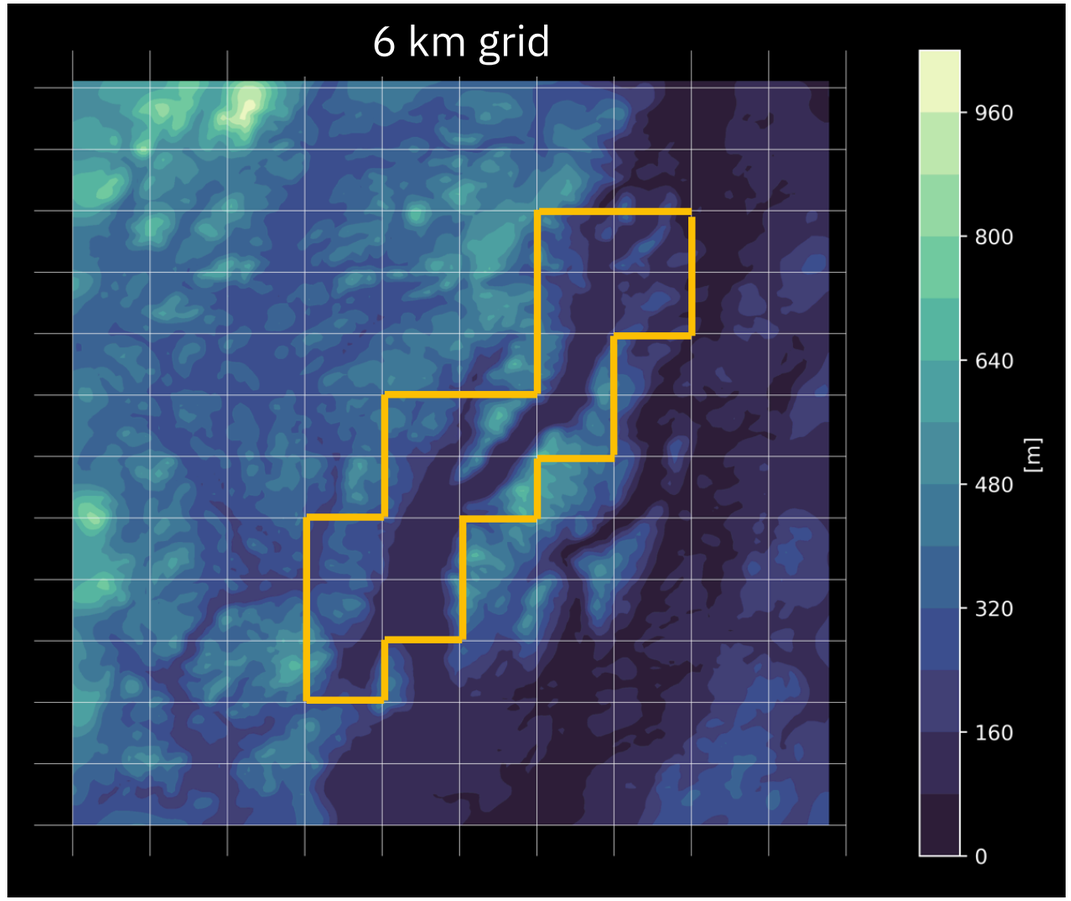
What weather model resolution is sufficient for medium-sized lakes and smaller?



GFS Model: 13 km
NAM Model: 12 km
RAP Model: 13 km



HRRR Model: 3 km (18 hrs)

Operational Weather Forecasts at Lake George

WRF/WRFDA v3.9.1

Four one-way nested domains:
9 / 3 / 1 / 0.33 km

Daily, operational forecasts of 36 hrs duration

Each forecast takes ~6 hrs on 160 cores

--> Can super-resolution help?

Over 3 years of daily forecasts at 0.33 km resolution

Aim: Reconstruct the WRF-simulated precip at 1 km resolution from the 9 & 3 km precip with efficient ML

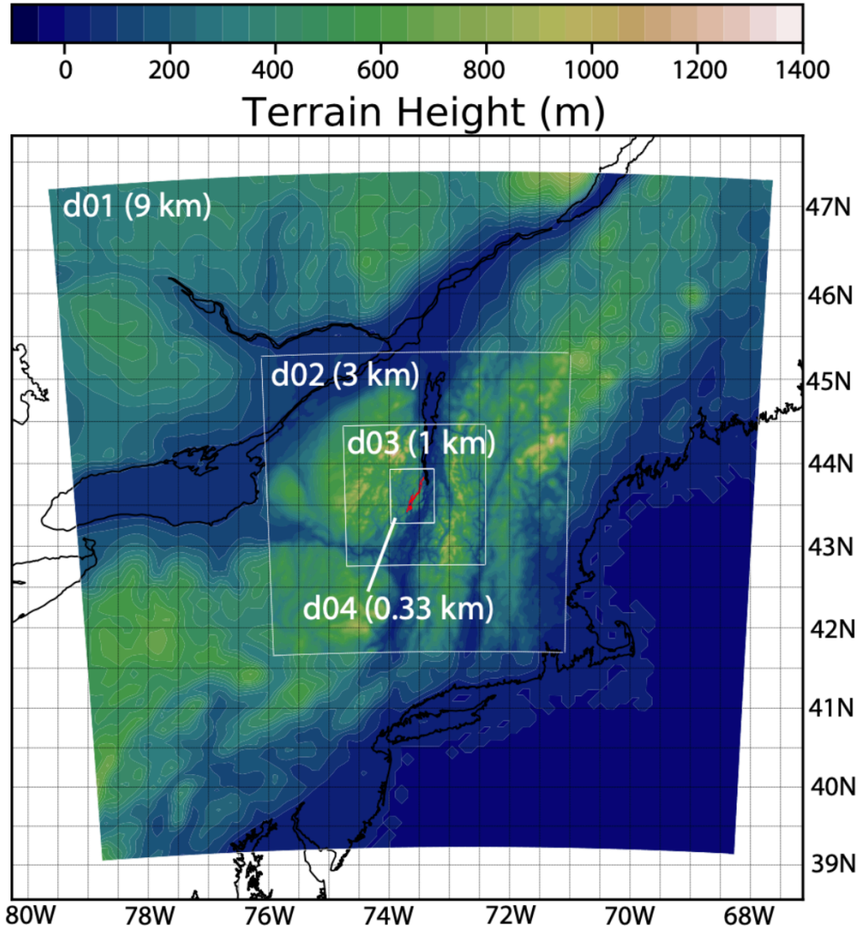


Figure 1: WRF model domains in northeast USA (Lake George is outlined in red). This manuscript uses WRF data from the three outer domains with 9, 3 and 1 km grid resolution.

Motivation

i) Reduce the use of energy-intensive weather simulations
ii) Create ensembles of weather forecasts for uncertainty quantification
ii) Scale global, high res weather & climate predictions without continuing need for huge supercomputers

Researchers have been exploring machine learning techniques downscale coarser resolution weather and climate simulations to finer resolution grids....

Regression based methods
Analog methods
Auto-regression methods
Deep neural network super-resolution based methods <-- *Focus of this work*

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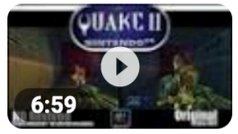

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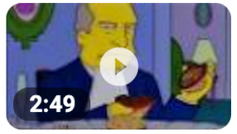

Upscale test with an unfinished Degrain+DeMPEG2 model. Show less Show more. Transcript. Up next ...
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ESRGAN

Enhanced super-resolution generative adversarial networks by Wang et al. [2019]

A deep neural network approach initially created for use with natural images which typically have no inherent resolution

Manepalli et al. [2020] used ESRGAN to reproduce the simulated power spectral density of near-surface winds at 2x resolution

We employed the SRResNet structure with the Residual-in-Residual Dense Block as basic blocks

Removed VGG and GAN loss to optimize for the prediction accuracy rather than visual quality (as suggested by Wang et al. 2019)

CAR

Content adaptive-resampler for image-based downscaling by Sun and Chen [2020]

The resampler network generates content adaptive image resampling kernels which are applied to the original high-resolution input to generate pixels on the downscaled image

Used the default configurations as proposed by Sun and Chen [2020]

TWO EXPERIMENTS

EXP 1: Feature values are 3 km WRF variables; target variable is 1 km WRF precipitation ***(3x downscaling)***

EXP 2: Feature values are 9 km WRF variables; target variable is 1 km WRF precipitation ***(9x downscaling)***

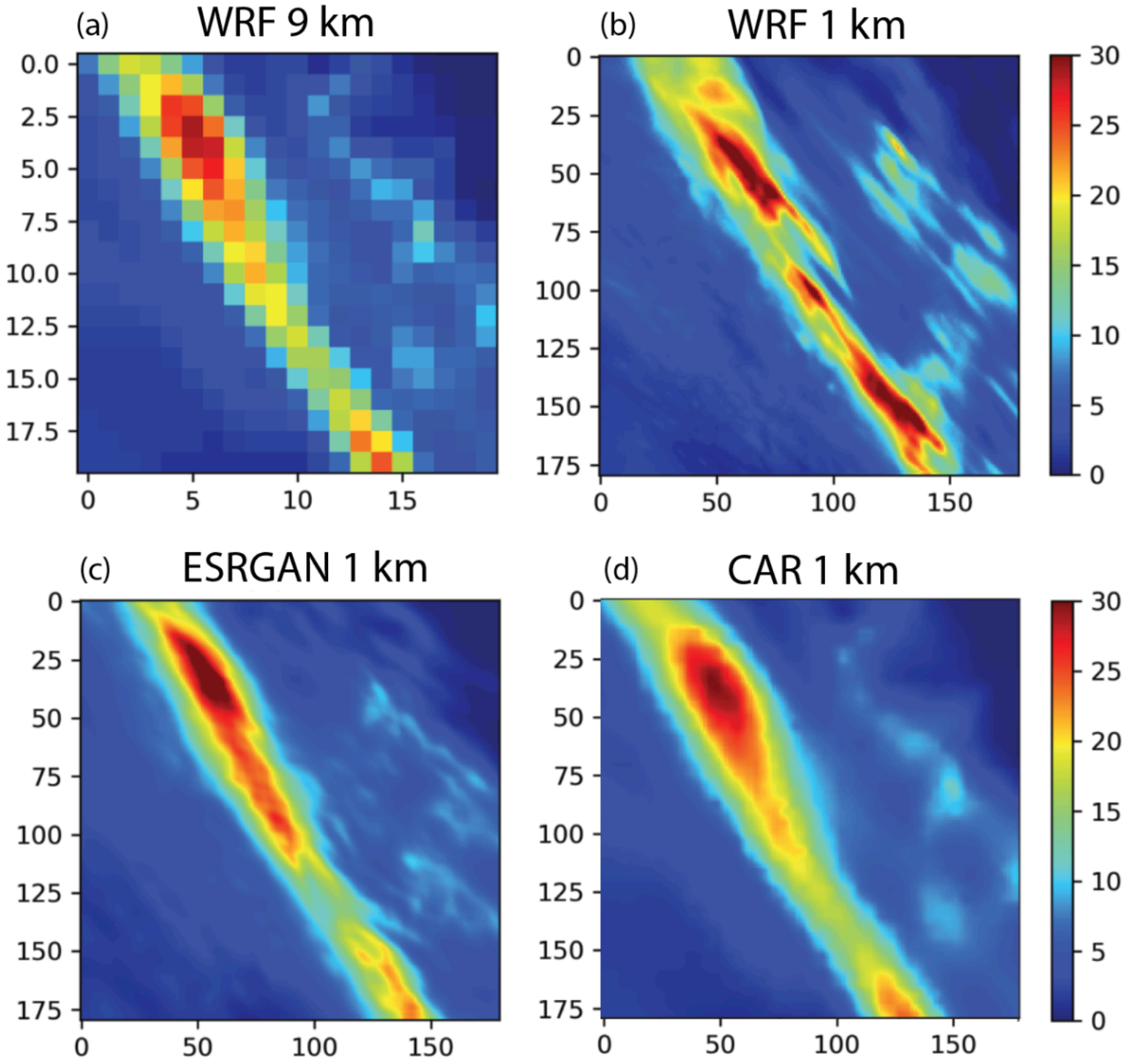

Figure 2: Example of precipitation reconstructions by the ESRGAN and CAR models from 9 km to 1 km horizontal resolution. The panels show accumulated precipitation (mm/hr) in the hour preceding 2019-11-01 04:00 UTC. (a) Original WRF precipitation from the 9 km domain; (b) original WRF precipitation from the 1 km domain (target); reconstruction by ESRGAN to 1 km resolution; and (d) reconstruction by the CAR model to 1 km resolution

Table 1: Mean absolute error using Bicubic, ESRGAN and CAR methods. The output grid resolution is 1 km, and the input grid resolution is listed in the table. The ESRGAN model has the best performance, followed by the CAR model. Both of the proposed models outperform the baseline bicubic interpolation.

Input grid resolution		Mean absolute error (mm/hr)		
		Bicubic	ESRGAN	CAR
EXP 1	3 km	0.83	0.040	0.384
EXP 2	9 km	1.98	0.078	0.931

ONGOING THOUGHTS…

Expand analysis to include additional variables, specifically near surface winds, surface humidity and downward short and long wave radiation. These are key inputs to hydrodynamic models.

Apply ESRGAN to **downscale GFS data from 25 km resolution to the 1 km WRF domain**. This is a particularly demanding task given the GFS model has different model parameterizations and dynamical core.

How transferable and generalizable is this approach? Manepalli et al. [2020] showed some success in this regard using ESRGAN to downscale winds, and is key to moving to climatic geographies.

How much data is required to adequately train the model? Here, we provided over nearly 2.5 years of hourly data for training – a prohibitive amount of simulation for larger geographic areas.