Spatiotemporal Super Resolution with Deep Generative Models for Creating Renewable Energy Resource Data under Climate Change Scenarios

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Background/Objectives. As we plan for a future with higher penetrations of renewables and increasing electrification, it becomes more important to understand how the electricity grid will operate under a variety of weather events. We must also consider that the weather our future grid will experience will be different and possibly more extreme than the historical weather that we have extensive data for. We can use data from global climate models (GCMs) to help understand how our climate may change over the next several decades, but there is often a significant gap between the low-resolution GCM data and the high-resolution weather data required to study power systems under specific weather events. Therefore, our objective in this work is to develop tools that can bridge this gap by using low-resolution GCM data to create realistic high-resolution weather datasets that can be used to study renewable energy generation and electricity demand.

Approach/Activities. To accomplish this objective, we have developed a set of generative machine learning models that can rapidly downscale GCM daily average output data at an approximate grid resolution of 100 km to hourly data at an approximate 4 km grid resolution. The models can be used to create high resolution data from nearly any GCM included in the Coupled Model Intercomparison Project (CMIP) Phase 5 or 6. Our methods include all datasets regularly used to study the integration of wind and solar power plants as well as changes in electricity demand due to heating and cooling loads. These models and datasets enable power systems modelers to study climate change-influenced weather events and their impact on the grid.

Results/Lessons Learned. We have downscaled and validated wind, solar, temperature, and humidity data with very promising results. The generative machine learning methods are computationally efficient and produce data that has similar statistical characteristics to current state-of-the-art historical datasets. We have trained initial generative models and produced an initial dataset collectively referred to as Sup3rCC: Super-Resolved Renewable Energy Resource Data with Climate Change Impacts. The data covers a (mostly) historical period from 2015-2025 and a future period from 2050-2059. We have also taken hypothetical high-electrification load data and scaled the heating and cooling loads with respect to the 2050-2059 high-resolution Sup3rCC meteorology. The results show how future levels of renewable energy generation and electrified load may be impacted by climate change, setting the stage for capacity expansion models to consider a dynamic climate through model years.