Downscaling Satellite Imagery for High Resolution Offshore Winds

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Abstract

The US offshore wind energy industry is in its early stages and has big plans for the future. Assessment of suitable locations for future wind farms relies on the availability of high resolution wind speed data. While in-situ observations from floating offshore buoys and wind masts give needed high resolution observations at specific locations, satellite imagery contains higher spatial and temporal coverage and has the potential to increase the amount of high resolution data available via downscaling techniques including traditional physics-based and statistical models as well as machine learning. Recent studies have shown that machine learning, in particular convolutional neural networks (CNN) from the field of computer vision, have shown to outperform traditional methods for downscaling tasks. In this analysis, multiple downscaling techniques applied to satellite derived wind speeds are compared and used for the prediction of wind speeds at an offshore buoy, aiming to demonstrate satellite imagery's potential for increasing the temporal availability of wind speeds at existing offshore buoys. Results show that CNNs show improved performance in downscaling satellite derived offshore winds over other downscaling methods including bilinear interpolation and random forest regression. The CNN model shows the most skill when including a kernel mean squared error (MSE) loss function and Leaky ReLU activation functions.

1. Introduction

Offshore wind energy is a low cost, green energy industry emerging around the United States. With only three offshore wind farms currently operational in US coastal regions totaling 110 megawatts (MW) of wind energy capacity, offshore wind energy remains a largely untapped resource of clean energy for US populations, ~40% of which live within proximity to the coast. To address the potential of this untapped resource, the US plans for the development of 30 gigawatts (GW) of offshore wind energy by 2030 and 15 GW of floating offshore energy by 2035 (Musial et al., 2023). While the US expands its offshore wind energy capacity, knowledge of high resolution wind speeds are increasingly necessary to plan for future locations of offshore wind farms. As in-situ observations obtained via floating offshore buoys and wind masts are costly to install on a large scale, other means of measurements are necessary to provide gap-free, long-term high resolution wind speeds in US coastal regions.

In many applications, high resolution winds are derived using traditional statistical and physics-based models to downscale wind speed products provided in lower resolution. While reanalysis products including the European Centre for Medium-Range Weather Forecasts ECMWF Reanalysis v5 (ERA5) are popular for offshore wind assessment, they are not as capable of predicting spatial patterns for wind as they are temporal patterns (Gualtieri, 2022). Furthermore, ERA5 tends to underestimate high winds above 10 m s^{-1} (Gandoin and Garza, 2024). In comparison, the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI) Blended Seawinds (NBSv2.0) contains winds speeds derived from multiple satellites in a blended product and shows increased capabilities in resolving high wind speeds compared to reanalysis products including ERA5 (Saha and Zhang, 2022), making it more ideal for offshore wind resource assessment.

In recent years, machine learning, with an emphasis on deep learning models from the field of computer vision, has demonstrated the ability to outperform traditional methods for downscaling climate variables. In addition to high accuracy, deep learning models are much faster at making predictions than physics-based models which have very high computational costs. As such, downscaling satellite derived wind speeds using a deep learning approach provides great potential for increasing the accuracy and knowledge of high resolution offshore wind resources. This analysis explores the potential of deep learning models for downscaling satellite derived wind speeds from NBSv2.0 to in-situ offshore buoys. This study aims to provide high resolution wind speeds at offshore buoys for the full time period of NBSv2.0 (July 1987 - present) allowing for long term wind resource assessment that would otherwise be limited to the duration of the buoy's deployment. Buoy 41002 South Hatteras maintained by the National Data Buoy Center (NDBC) is used as the high resolution target in this analysis.

2. Literature review

In recent years, machine learning has been increasingly leveraged for many applications of downscaling and spatial interpolation of climate variables. A simplistic approach of using the random forest for spatial interpolation takes the k-nearest observations and their distances from a given target location as inputs (Sekulić et al., 2020). For case studies in precipitation and temperature, this model was shown to outperform kriging and inverse distance weighting.

Further, the skill of convolutional neural networks has been demonstrated in many cases of reconstructing high resolution grids and downscaling climate fields to in-situ observations. The Wasserstein GAN with Gradient Penalty showed skill in downscaling u and v components of wind from low resolution ERA-interim reanalysis (80 km) to high resolution Weather Research and Forecasting (WRF) simulations (10 km) and demonstrated that the addition of low resolution covariates allows for better performance of the GAN when applied to climate fields (Annau et al., 2023). A convolutional LSTM model using ResNet encoders and decoders outperformed optimal interpolation (OI) in reconstructing high resolution (7.5 km) maps for sea surface height (SSH) by spatially and temporally interpolating missing regions of observations between satellite altimeter tracks and using gridded sea surface temperature (SST) as a high resolution covariate (Martin et al., 2023). A wind convolutional neural network including transformers (WCT) was developed to downscale climate conditions including 26 variables from coarse resolution (220 km x 280 km) general circulation models (GCM) to wind speeds at four land based weather stations in New Jersey and Pennsylvania (Gerges et al., 2023). The WCT outperformed other machine learning methods including random forest regression, support vector regression, and various neural networks including CNN, LSTM, and transformers. A hybrid CNN (HCNN) model made use of both global and local predictors to downscale sea states to a buoy in the Bay of Biscay and showed comparable results to data from the RESOURCECODE hindcast database (Michel et al., 2022).

While many applications show the skill of CNNs in downscaling and spatial interpolation of climate variables, most use climate models and reanalysis data as the low resolution model input. This study instead shows the potential of downscaling gridded, long-term satellite derived wind speeds to in-situ measurements using CNNs, which has previously not been done to my knowledge.

3. Methodology

3.1. Data

3.1.1 Blended Seawinds (NBSv2.0)

The National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI) Blended Seawinds (NBSv2.0) contains surface wind speeds globally gridded with a 0.25° spatial resolution dating from July 1987 to present at a 6-hourly, daily, and monthly resolution. The data is blended from 17 satellites, with up to 7 at a time, allowing for the product to resolve extreme wind speeds with higher accuracy than other wind based products (Saha and Zhang, 2022). NBSv2.0 is currently archived at NCEI with both near-real time and science quality post-processed formats from the NOAA CoastWatch server (https://oceanwatch.noaa.gov/cwn/products/noaa-ncei-blended-seawinds-nbs-v2.html).

3.1.2 National Data Buoy Center (NDBC)

The National Data Buoy Center (NDBC) provides a collection of marine in-situ observations around the globe. Buoy 41002 South Hatteras located at 31.759 N 74.936 W (Fig. 1) is maintained by NDBC (https://www.ndbc.noaa.gov/station_page.php?station=41002) and provides historical continuous surface wind speeds from 1989 to 2018 with a 10-minute resolution. As buoy 41002 has a higher time resolution than NBSv2.0, the wind speeds at buoy 41002 were averaged into 6-hourly time steps at 00:00:00, 06:00:00, 12:00:00, and 18:00:00 to align with the 6-hourly time resolution of NBSv2.0.

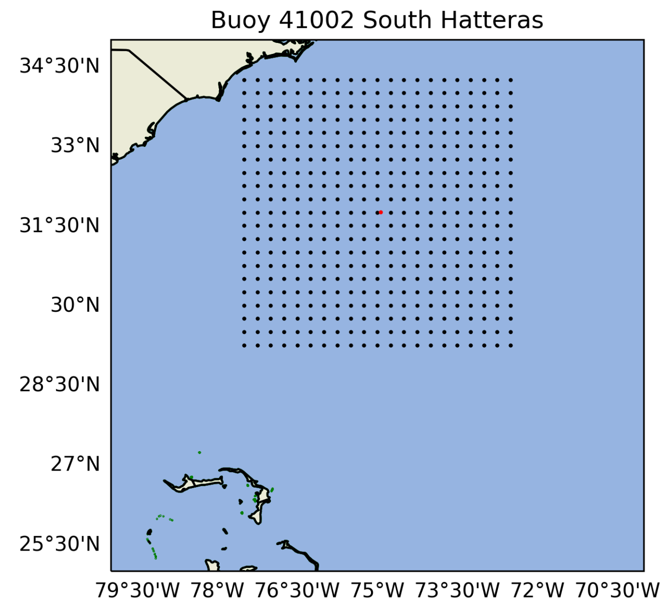

Figure 1: Locations of NDBC buoy 41002 (red) and nearby NBSv2.0 (black) observations.

3.2. Models

Multiple methods were compared for the downscaling task in this analysis. The simplest method takes the nearest gridded NBSv2.0 observation as a proxy for the buoy wind speed measurements. The bilinear interpolation algorithm was employed to further account for the spatial context, giving a weighted sum of the nearest four observations. Further, random forest regression (RFR) was used for spatial interpolation with the k-nearest observations given as features to predict the buoy wind speeds, similarly as done in Sekulić et al., 2020. For this analysis, k was set to 9 to have a 3x3 grid of inputs surrounding the buoy as no further grid points showed to increase model accuracy for the RFR. As the distances of the nearest observations in this analysis do not change due to the input being the same grid for each observation, distances to the nearest observations were not included as input parameters into the RFR. The final downscaling method tested in this analysis is convolutional neural networks (CNN) which have shown the most promise for downscaling tasks.

3.3. Training Procedure

3.3.1 Random Forest

For the RFR, 5-fold cross validation was used to tune the hyperparameters and final performance was assessed on an independent test set. To avoid information leakage in the time series, the folds were not randomly shuffled, and instead were split evenly throughout the time periods (Fig. 2) with 15 day windows added between sets to avoid training and testing on consecutive observations within the time series. The training data contains 23,757 observations and the test set, taken as the last year of provided data, contains 1635 observations.

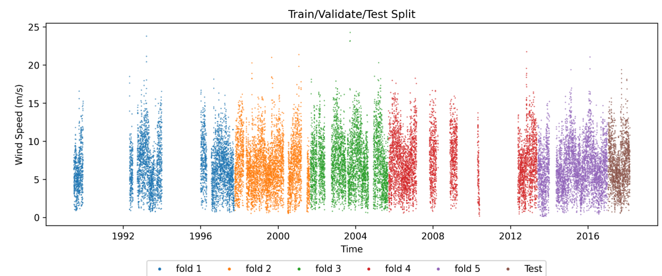

Figure 2: Buoy 41002 time series and folds used for the RFR model.

The hyperparameters tuned for the RFR are the number of trees and minimum samples per leaf. Final values chosen are 500 trees and 30 minimum samples per leaf which minimize out of bag error (Fig. 3). The number of input parameters to be considered for a split in the model is set to 3 as a value of p/3 is suggested for regression where p is the total number of inputs.

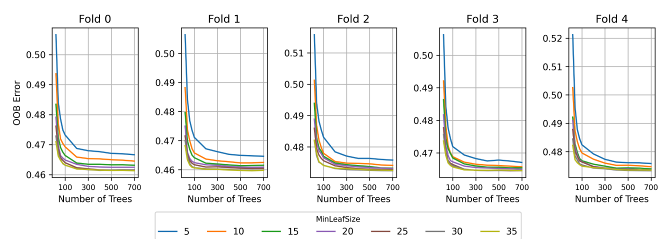

Figure 3: Out of bag (OOB) error for number of trees and minimum samples per leaf for the RFR.

3.3.2 Convolutional Neural Networks

For the CNN models, the first four folds from the RFR training were combined to create one train set (19,016 observations) with the fifth fold being used as the validation set (4741 observations). The last year of data is taken as the test set (1635 observations). As CNNs require small values for numerical stability and fast computation time, both normalization and standardization were implemented separately and results for both preprocessing methods were compared. In the case of normalization, both NDBC buoy 41002 and NBSv2.0 data were scaled to have values between zero and one. As wind speeds approximately follow a weibull distribution (Monahan, 2005), a box cox transform was first applied to both NDBC buoy 41002 and NBSv2.0 to remove the skewness of the data before standardization.

While the WCT deep learning model proposed for downscaling GCMs to weather stations (Gerges et al., 2023) provides a framework with promise for this application, no code is provided alongside the research. In addition, the model is developed using 26 inputs each with their own pipeline. Due to the lack of code availability and in order to reduce the amount of training time required, a new CNN model is developed for this analysis and only takes NBSv2.0 as input. This analysis uses the TensorFlow and Keras python libraries for constructing the model and Google Colab's T4 GPU instance for training the model. The architecture of the model is given in Fig. 4. The model uses the Adam optimizer with a learning rate of 1e−5 and batch size of 256. Two loss functions are considered and compared in this analysis. The first loss function is mean squared error (MSE). The second is a kernel MSE loss function derived from a gaussian kernel (Eq. 1).

$$L_{K-MSE} = \sum_{t=1}^{N}\left[1 - exp\left\{-\left(y_t - \hat{y}_t\right)^2/2\sigma^2\right\}\right] \quad (1)$$

The kernel MSE was chosen as it has shown promise as a loss function in deep learning applications in wind speed forecasting due to its robustness against nonlinearity in errors (Chen et al., 2022). In addition, the kernel MSE shows robustness against outliers, allowing it to more accurately capture extreme wind speeds. σ is set to $\sqrt{2}/2$ in this analysis as done in Chen et al., 2022. Activation functions considered in this analysis are the rectified linear unit (ReLU) and Leaky ReLU. Results are shown for three cases of the CNN model. The first case uses data normalized between zero and one along with MSE loss and ReLU activation functions. The second case standardizes the data and similarly uses MSE loss and ReLU activation functions. The third case standardizes the data and uses the kernel MSE loss and LeakyReLU activation functions. Each case was trained on a number of epochs that minimized the respective loss function: 10 for case 1, five for case 2, and three for case 3 (Fig. 5). More trials with more epochs showed an increase in validation loss past these number of epochs.

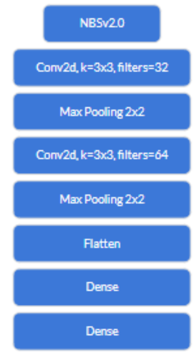

Figure 4: CNN Architecture. The final dense layers have 10 and 1 node respectively. The output dense layer uses a linear activation function.

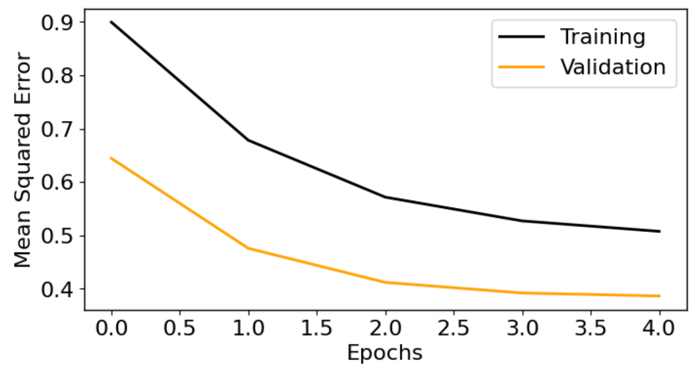

Figure 5: Training loss for case 2 CNN. Similar results are obtained for cases 1 and 3 for their respective number of epochs.

4. Results

Bias, root mean squared error (RMSE), and mean absolute error (MAE) were evaluated for all models to compare the accuracy of each downscaling method (Fig. 6). Unsurprisingly, taking the nearest NBSv2.0 observation as a proxy for buoy wind speed measurements performed the worst out of all methods. Bilinear interpolation performed almost identically to taking the nearest observation with a marginal decrease in errors of ~0.01 m s^{-1} in each metric. Due to the location of NDBC buoy 41002, the weights of the nearest two NBSv2.0 observations are 0.72 and 0.25 while the weights of the further two observations are 0.03 and 0.01. As such, it is clear that bilinear interpolation is not very suitable for the location of the buoy relative to the nearest NBSv2.0 observations as 97% of the weighting comes from only two of the four neighboring points, with the majority 72% coming from just one neighboring point.

All machine learning methods implemented show improvement over the simpler proxy method and bilinear interpolation. All models show a decrease of at least 0.77 m s^{-1} in bias, 0.27 m s^{-1} in RMSE, and

0.14 m s^{-1} in MAE over using the nearest NBSv2.0 observation as a proxy (Table 1). The RFR and the case 1 CNN performed similarly with the RFR having slightly lower bias and RMSE and the case 1 CNN having slightly lower MAE. The case 2 and case 3 CNNs outperformed all other models, showing that standardizing the inputs to the CNN yields the highest accuracy in this application.

Decrease from Nearest	RFR	CNN 1	CNN 2	CNN 3
Bias	0.86	0.77	0.91	0.85
RMSE	0.27	0.31	0.39	0.36
MAE	0.17	0.14	0.24	0.23

Table 1: Decrease in errors of each machine learning model compared to using the nearest observation. Units are in m s^{-1}.

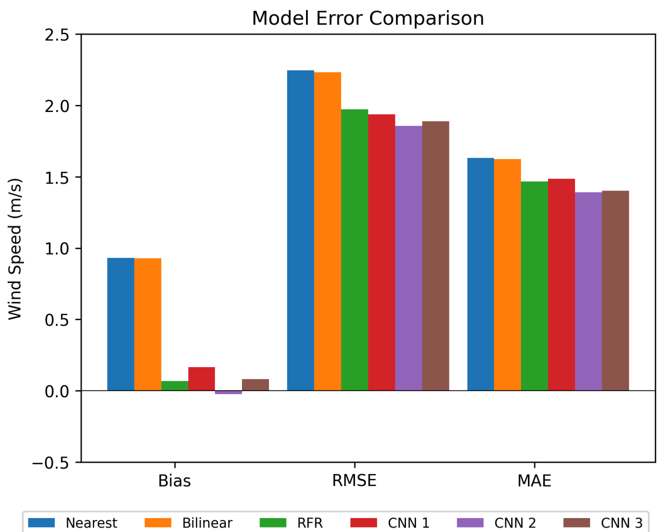

Figure 6: Bias, root mean squared error (RMSE), and mean absolute error (MAE) for all models. CNN 1 corresponds to the model with inputs normalized between zero and one. CNN 2 corresponds to the model with standardized inputs using ReLU activation functions and MSE loss. CNN 3 corresponds to the model with standardized inputs using leaky ReLU activation functions and Kernel MSE loss.

While the case 2 CNN using MSE loss and ReLU activations yields slightly lower overall errors than the case 3 CNN using kernel MSE loss and Leaky ReLU activations, the latter contains more realistic properties for prediction. The model using kernel MSE loss predicted high wind speeds with higher accuracy on the test set demonstrating its robustness to outliers compared to MSE loss (Fig. 7). When using kernel MSE loss, a maximum wind speed prediction of 18.36 m s^{-1} is achieved on the test set compared to a maximum wind speed prediction of 16.32 m s^{-1} when using MSE loss. In addition, Leaky ReLU allowed the model to predict low wind speeds with higher accuracy giving a minimum wind speed prediction of 1.25 m s^{-1} over the test set compared to a minimum wind speed prediction of 1.84 m s^{-1} when using ReLU activations (Fig. 7).

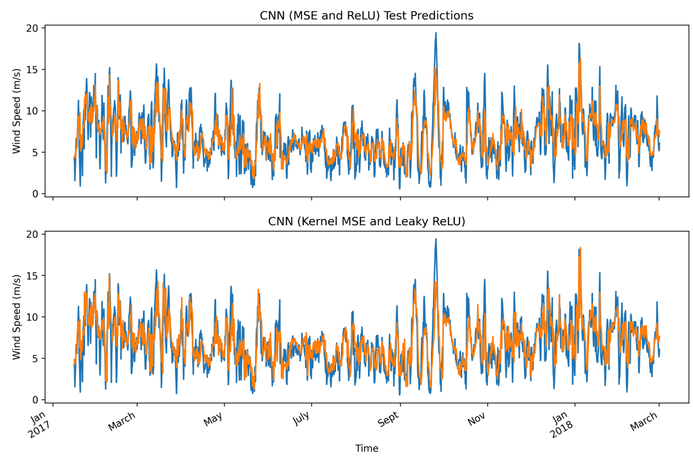

Figure 7: Time series comparison of CNN predictions (orange) to buoy wind speeds (blue) over the test set.

The benefits of kernel MSE loss and Leaky ReLU activations to the model are demonstrated further when predicting wind speeds over the full time series of the NBSv2.0 satellite product (Fig. 8). When using kernel MSE loss, 62 values in the missing time series are filled with wind speeds over 15 m s^{-1} compared to only 32 values over 15 m s^{-1} when using MSE loss. Further, the maximum wind speed prediction increases to 20.39 m s^{-1} when using kernel MSE loss compared to 18.59 m s^{-1} when using MSE loss. When using Leaky ReLU, 347 predictions were made below 2 m s^{-1} compared to only 117 predictions when using ReLU. In addition, the minimum wind speed prediction decreased to 0.45 m s^{-1} from 1.09 m s^{-1} when using Leaky ReLU in place of ReLU. The extended range of wind speed predictions determines that the case 3 CNN using Leaky ReLU and Kernel MSE loss is preferred to the case 2 CNN which had the lowest overall errors.

Further analysis of the interpolated time series shows that two of the highest predicted values for the CNN models, August 28, 2011 and September 13, 2018, correspond to hurricanes Irene and Florence passing over the buoy, respectively. This demonstrates the capability of CNNs to downscale wind speeds during extreme events and shows that these high wind speed predictions are not anomalous errors. However, hurricane strength wind speeds must be at least 33 m s^{-1}, so these extreme values while predicted are still underestimated. This results from the buoy not accurately recording hurricane strength winds in the training data as no training observations having wind speeds above 25 m s^{-1}, even though many of the high wind speeds recorded by the buoy happened during hurricanes. As high winds are still predicted during hurricanes not observed by the buoy, the CNN model shows promise in accurately downscaling hurricane strength wind speeds from NBSv2.0 given more accurate high resolution input for extreme events.

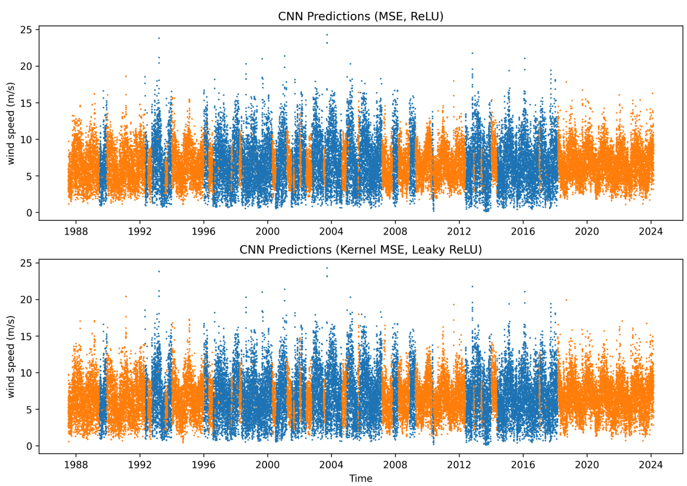

Figure 8: Full time series at buoy 41002 with observed wind speeds (blue) filled in with CNN predictions (orange).

5. Conclusion

This study shows the skill in machine learning methods, in particular deep learning convolutional neural networks, in downscaling wind speeds from satellite imagery to the locations of in-situ observations. While it was clearly shown that CNNs outperformed all other methods in the analysis, further improvements were made to the CNN with the inclusion of Leaky ReLU activation functions and kernel MSE loss, which allowed the model to more accurately estimate low and high wind speeds, respectively. Further research could expand upon the number of stations used in this analysis and compare model performance in different coastal regions. In addition, comparisons of downscaling wind speeds from same resolution reanalysis products and satellite derived winds can provide more insight into the potential increase in high resolution wind speed accuracy that may be obtained from downscaling satellite imagery compared to reanalysis products.

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