Statistical Spatial and Temporal Downscaling of Meteorological Data for Water Quality Forecasting Model at Falling Creek Reservoir

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Introduction

As part of a pilot study of water quality forecasting, researchers in our lab at Virginia Tech are implementing the General Lake Model (GLM) to forecast meteorological variables related to water quality at Falling Creek Reservoir, Virginia. Lab members use the GLM, a one-dimensional hydrodynamic lake model (Hipsey et al., 2017) to make daily forecasts of water temperature and the likelihood of lake turnover, both of which relate to the concentration and distribution of contaminants. The lab plans to additionally forecast algae populations in the future.

The GLM requires input data for the environmental drivers of lake processes which we can commonly measure, often continuously. These include meteorological variables such as ambient air temperature, incoming surface shortwave and longwave radiation, average wind speed, and relative humidity. Past site measurements and future meteorological forecasts drive the model and forecast water temperature at the same depths at which physical samples are taken. Falling Creek Reservoir is equipped with sensors that measure local meteorology precisely and frequently. In contrast, the meteorological forecasts used to drive the model in simulations of the future are at a coarse resolution, and are not specific to the study site. To maximize the success of environmental forecasting, input data should be as accurate as possible and any uncertainties in the input data should be quantified. The currently available meteorological forecasts do not necessarily meet these criteria. To address this issue, I developed and implemented a workflow to spatially and temporally downscale 16-day NOAA GEFS meteorological forecasts to the specific site, Falling Creek reservoir.

Methods

Overview

Using site-specific observational data and coarse-scale GEFS forecasts, I calculated model coefficients for the linear relationship between the observational and forecast data for five meteorological variables: air temperature, relative humidity, wind speed, downward shortwave radiation flux, and downward longwave radiation flux. I later used these relationships later to spatially downscale forecasts. Next, I temporally downscaled the training data from 6-hourly to hourly and calculated the total standard error resulting from the spatial and temporal downscaling processes. The last two weeks of data were withheld from the training dataset, and I instead downscaled forecasts over this time period. I then compared the resulting downscaled forecasts and the original forecasts prior to downscaling to observational data to assess whether downscaling made the forecasts more accurate.

Data

Observational data was retrieved at the minute-scale from an on-site meteorological station established by researchers starting in late April of 2018. Table 1 shows the instruments associated with each meteorology variable of interest. Outputs from the NOAA Global Ensemble Forecasting System (GEFS) model were used as the meteorology forecasts. The GEFS forecasts have a spatial resolution of 1 degree latitude by 1 degree longitude and a temporal resolution of 6 hours. Each forecast predicts 16 days into the future and is comprised of 21 ensemble members representing uncertainty in starting conditions. The NOAA forecast represents meteorological variables which are fluxes, shortwave and longwave radiation, as averages over the previous 6 hours, and states variables as predictions at 6-hour intervals. Because the least uncertainty exists at the beginning of the 16-day forecasts, only the first 24 hours of each GEFS forecast were included in the training dataset.

Table 1. Utilized sensor capabilities

On-Site Sensors	Meteorological variable	Precision
HC2S3 Temperature and Relative Humidity Probe	Air Temperature at 2m	-50 - 100℃ ± 0.1
	Relative Humidity at 2m	0 - 100% ± 1.3
Wind Monitor	Wind Speed at 10m	0 - 100 m/s ± 0.3
Hukseflux Net Radiation	Surface Downward Shortwave Radiation Flux	0 - 2000 W/m² ± 10%
	Surface Downward Longwave Radiation Flux	0 - 1000 W/m² ± 10%

Parameter Fitting

I fit the model coefficients for spatial downscaling according to the linear relationship between observational data and forecasts in the training dataset. Although meteorological variables are required at hourly resolution for the GLM model, I started by aggregating the minute-scale observational data and 6-hourly GEFS forecasts to the daily scale. I did this because there was a greater signal in the relationship between observations and forecasts at the daily scale than subdaily scale, where observational noise was high. Using linear regression, I related the observations and forecasts for each of the meteorological variables. I applied a linear transformation to each meteorological variable of the training data to reduce bias in the forecasts (i.e., the debias step).

After spatially debiasing, I downscaled the forecasts from daily resolution to hourly resolution. To temporally downscale shortwave radiation, I redistributed the daily downscaled value according to a solar geometry function (Dietze, 2017) that incorporates site-specific diel and seasonal solar patterns. To downscale air temperature, relative humidity, and average wind speed, I started by redistributing the spatially downscaled daily average according to the original pattern in the original GEFS forecasts. I did this by calculating the relative difference between each original 6-hourly NOAA forecast and the average for that day, then added that value to the spatially debiased daily averages. I did this to retain some of the information from the sub-daily forecast values, while still preserving the daily average of the spatially debiased values. After redistributing to 6-hourly values, I interpolated to hourly resolution the monotone piecewise cubic interpolation method. Unlike the other metrics, I did not downscale longwave radiation to the hourly resolution. Because longwave radiation is a flux, not a state, the information from GEFS forecasts represents an average of the 6-hour period. Without a known relationship to redistribute longwave across the day, as was the case with shortwave, the 6-hourly average is insufficient information to temporally downscale to an hourly resolution. For these reasons, longwave is left at the daily resolution at this time. The methods of temporal downscaling are summarized in Table 2.

Table 2. Temporal Downscaling by meteorological variable

Meteorological variable	Method of temporal downscaling
Air Temperature at 2m	Interpolation
Relative Humidity at 2m	Interpolation
Wind Speed at 10m	Interpolation
Shortwave Radiation Flux	Solar Geometry
Longwave Radiation Flux	None

After downscaling the training data, I calculated the standard deviation of the residuals from linear regression between observational data and forecast data for later use as a downscaling noise addition term. For longwave, I calculated this after the spatial debiasing step because that was the last step. For the other meteorological variables, I calculated this after the spatial and temporal downscaling steps were complete. The steps for the overall parameter fitting process are summarized (figure 1).

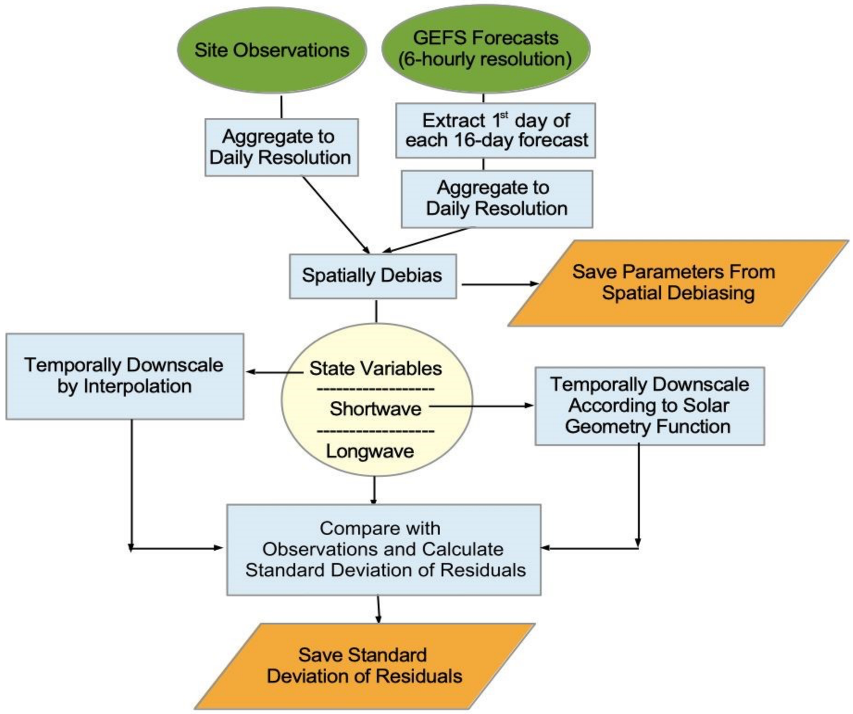

Figure 1. Flowchart of parameter-fitting steps.

Downscaling Future Forecasts

After fitting the model coefficients, I downscaled a 16-day GEFS forecast over the period of time withheld from the training dataset, according to the following steps. As in the model fitting process, I aggregated the forecasts to daily resolution. Then, I used the saved model coefficients from the spatial downscaling of the training data to spatially downscale the forecasts at the daily resolution. Next, I created a version of the ensemble members with added random noise sampled from a normal distribution with error equal to the standard error previously calculated for each meteorological variable. I then temporally downscaled these ensemble members according to the methods previously described in the fitting process.

Evaluation

To evaluate the downscaling process, I compared two weeks of downscaled forecasts and two weeks of non-downscaled forecasts against observational data. An “out-of-the-box” implementation of the GEFS forecasts which is the current form of input in the lake water quality forecasting served as a control to compare the downscaled forecasts against. In this “non-downscaled” version, 6-hourly GEFS forecasts of physical states were linearly interpolated to the hourly scale. The 6-hourly longwave and shortwave values were repeated over the preceding 6 hours that the forecast is associated with.

Next, I performed steps to evaluate the downscaling process. I calculated R^2 values for the linear relationship between forecasts and observations to determine the strength these relationships by variable. I calculated the average difference between downscaled forecasts and observational data for each meteorological variable to determine average bias in downscaled forecasts. To assess the effectiveness of the confidence interval created by forecast ensemble members, I calculated the percentage of observations that fell within the bounds of forecasted values. I evaluated the performance of the downscaling in these three ways using a series of 1-day forecasts spanning 14 days. I downscaled only the first day of each GEFS to evaluate the downscaling process, because error in short-term forecasts are more reflective of the error from downscaling than long-term forecasts, which have greater propagation of GEFS noise through time.

Results

The results are broken into four categories: (1) model parameterization (2) relatedness of downscaled forecasts and observations, (3) the bias in the forecasts, and (4) the representation of error in the forecasts.

Model Parameterization

The results of the parameter fitting process are shown in Table 3 below. The slope, intercept, and R 2 of the linear spatial debiasing at the daily resolution are shown for each meteorological variable. The R 2 for air temperature, shortwave radiation, and longwave radiation were particularly high at the daily resolution. While the R 2 for air temperature, relative humidity, and wind speed all decreased by more than 0.1, the R 2 for shortwave radiation remained nearly the same after temporal downscaling. Wind speed forecasts were poorly correlated with observations at the daily resolution and especially at after temporal downscaling to hourly resolution. The standard deviation of residuals from downscaling shortwave radiation were particularly high.

Table 3. Downscaling parameter fitting results

	Slope	Intercept	R^2 after daily spatial debiasing	R^2 after spatial & temporal downscaling	Standard deviation of residuals after downscaling
Air Temperature	0.96	13.1	0.95	0.78	3.29
Relative Humidity	1.08	-8.3	0.62	0.51	13.1
Wind Speed	0.53	0.67	0.43	0.14	1.13
Shortwave Radiation	0.78	6.18	0.82	0.78	129
Longwave Radiation	1.00	26.4	0.94	NA	10.6

Correlation between Forecasts and Observations

The R-squared values in Table 4 describe the strength of the linear relationships between the mean downscaled value and the site observations at each time step for two weeks of 1-day forecasts. The “not downscaled” scenario represents the out-of-the-box implementation of the GEFS forecasts we currently use in the GLM, while the downscaled version represents results after spatial and temporal downscaling. Downscaling improved the correlation between forecasts and observations for all meteorological variables except wind speed. The improvement in shortwave radiation forecast skill was quite drastic, increasing from an R^2 of 0.19 to an R^2 of 0.88. A scatterplot comparing the downscaled ensemble averages against the site observations is shown (figure 3) to provide an example of a visual representation of the correlation. Scatterplots of the remaining meteorological variables are shown in figure 1 of the appendix.

Table 4. Mean R^2 values of hourly comparison, first day of forecasts

	Air Temperature	Shortwave Radiation	Relative Humidity	Wind Speed
Not downscaled	0.28	0.19	0.23	0.20
Downscaled	0.48	0.88	0.48	0.13

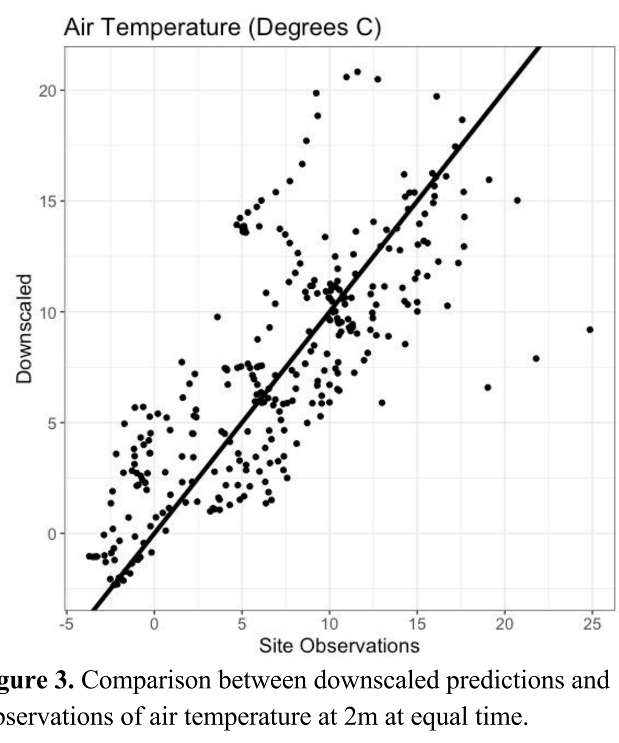

Figure 3. Comparison between downscaled predictions and observations of air temperature at 2m at equal time.

Comparison of Mean Error

Another important factor when considering the performance of the downscaling process is the bias present in the results. The average difference between forecasts and observations are shown in Table 5 for the downscaled and "not downscaled" scenarios. A value of 0 would imply that there is no overall bias in the forecasts, while progressively higher values indicate increased bias. As expected, the average magnitude of bias decreased for each of the meteorological variables after downscaling. The decrease in bias of temperature, shortwave radiation, and longwave radiation were quite substantial, decreasing from an average bias of 2.44°C to 0.64°C, 25.2 W/m² to 3.9 W/m², and -34.0 W/m² to -5.6 W/m², respectively.

Table 5. Average of forecast error (forecast minus observations)

	Air Temperature	Shortwave Radiation	Relative Humidity	Wind Speed	Longwave Radiation
Not downscaled	-2.44°C	25.2 W/m²	10.7%	0.48 m/s	-34.0 W/m²
Downscaled	0.64°C	3.9 W/m²	7.8%	-0.11 m/s	-5.6 W/m²

Assessment of "Confidence Intervals" of Ensembles

The last form of evaluation of the downscaling process I used was to consider the accuracy of the confidence interval of the forecasts, or the spread between the predictions of all the ensemble members. If the ensembles are truly representative of uncertainty in the forecasts, it would be expected that about 90% of observations fall within the middle 90% of ensemble members, and nearly 100% of observations would fall within the outer limits of the ensemble members. Table 6 summarizes the percentage of observations that fall within the total spread of ensemble members across all time steps from each of the repeated 1-day forecasts. The range of downscaled air temperature and wind speed ensemble members contained about 90% of hourly observations, while the ensemble members of shortwave radiation about 80% of the observations. All downscaled meteorological variables improved the representation of observed conditions compared to the non-downscaled scenario.

Table 6. Percentage of observations contained within range of ensembles

	Air Temperature	Shortwave Radiation	Relative Humidity	Wind Speed	Longwave Radiation
Not downscaled	18.1%	26.7%	8.5%	22.7%	17.1%
Downscaled	97.2%	82.2%	92.3%	98.8%	86.2%

The downscaled ensemble for air temperature and shortwave are shown (figure 4). The ensemble members of temperature and shortwave both cover a relatively large range. Some shortwave ensemble members reach values greater than 1,500 W/m² which are not feasible. Representations of the remaining meteorological variables are shown (Appendix, figures 2-4).

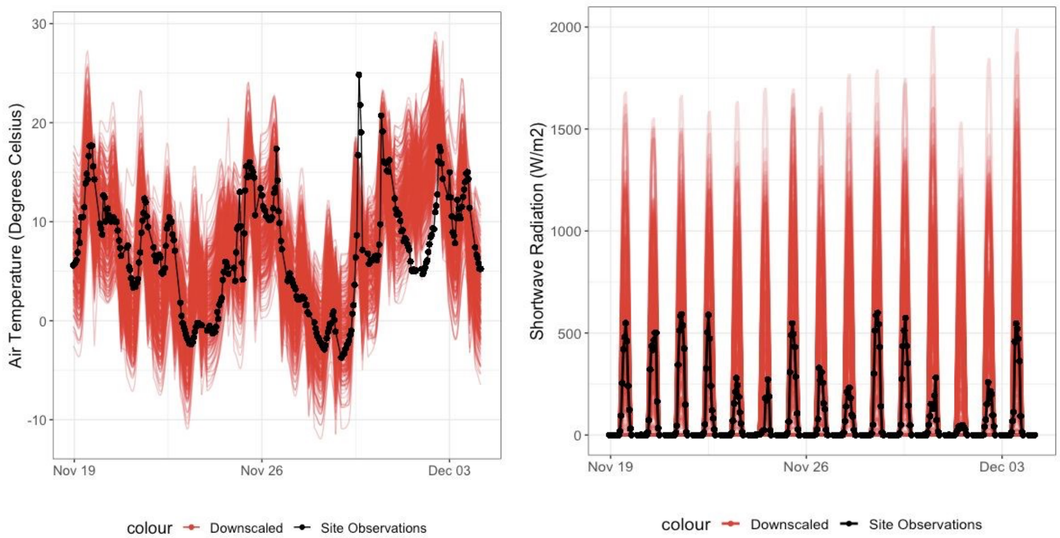

Figure 4. Observed air temperature at 2 meters and 1-day predicted forecasts over a late-fall 14-day period (left). Observed shortwave radiation flux and 1-day predicted forecasts (right).

Discussion

Overall, this downscaling process substantially improved the representation of meteorological forecasts for use in the GLM at Falling Creek Reservoir. The correlation between forecasts and observations was strengthened for air temperature, shortwave radiation, and relative humidity when spatially and temporally downscaled. There was not a strong relationship between forecasted average wind speed and downscaled average wind speed, likely because wind speed behaves more stochastically than the other variables. The downscaling process reduced the bias in forecasts for all variables, which an important result, because bias in the meteorological input data could cause bias in the GLM output. The noise addition step should be refined because some ensemble members reach unfeasible values, as is the case for shortwave radiation flux.

Now that we have developed the general workflow for the downscaling process, future work can further improve our framework and its results. For all meteorological variables, we used a simple linear regression for spatial downscaling. Researchers have successfully implemented other forms of statistical downscaling in other studies such as canonical correlation analysis and even artificial neural networks (Deka, 2017). One benefit of our approach is that it is highly flexible, in addition to being relatively accurate. Beyond the linear model, different methods of spatial downscaling are available, and an evaluation process can be helpful to identify what works best for each meteorological variable.

In addition to adapting the downscaling model, we can use more informed methods of noise addition. Currently, we add random noise independently for each meteorological variable.

However, there is known covariance between meteorological variables. For example, unexpected cloudiness would cause a decrease in both shortwave radiation and air temperature. If we can incorporate the covariance between meteorological variables, we could account for such circumstances and provide ensemble members that represent more realistic variation among meteorological variables.

While there are ideas for improvement, our downscaling process has already shown substantial improvement over the non-downscaled option. Future work could further improve accuracy and robustness of the downscaling process. Once integrated into the water quality forecasting project, more analysis should be done to further quantify the effect of downscaling meteorology forecasts in the water quality forecasting framework.

References

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Appendix

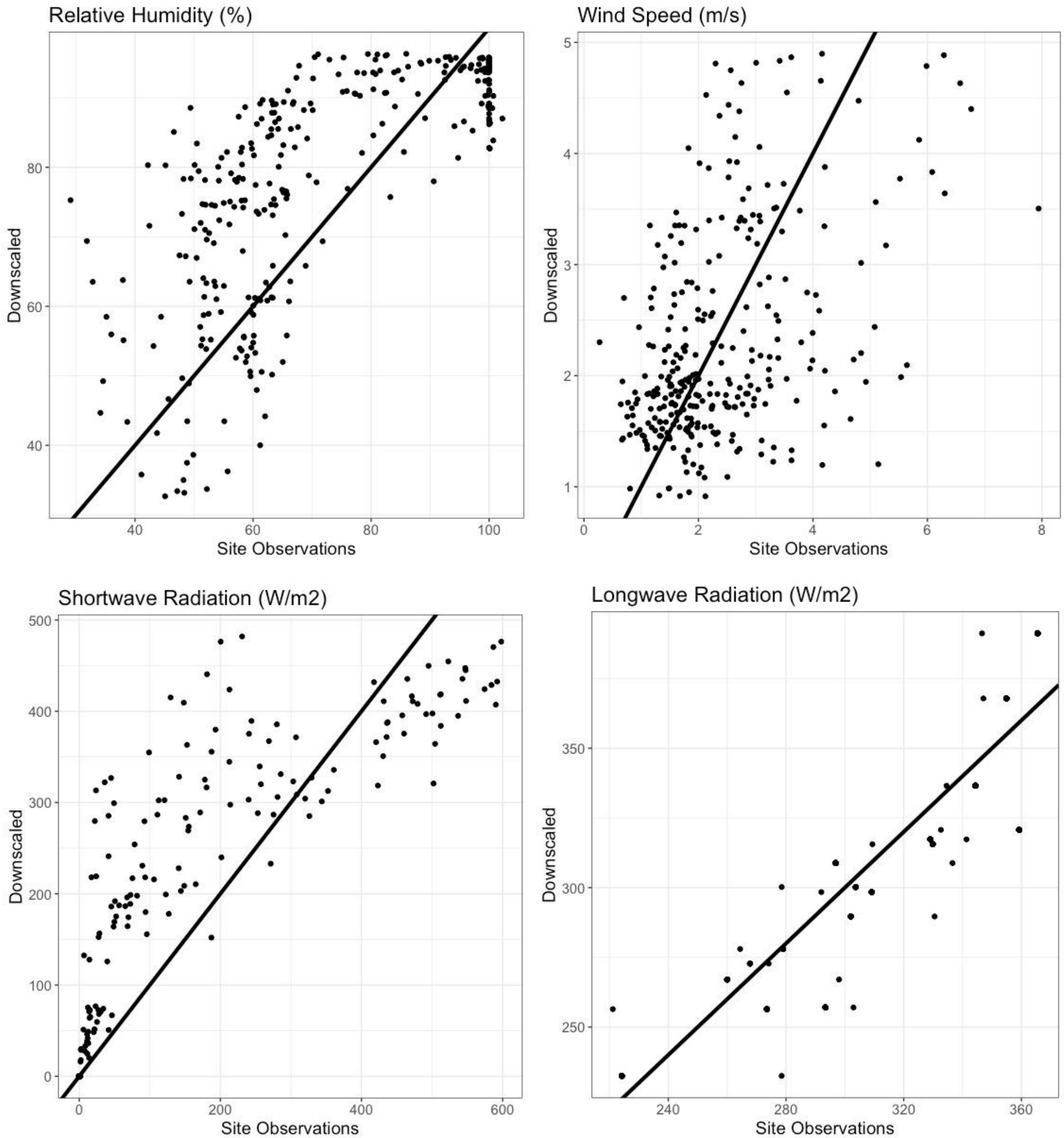

Figure 1. Comparison between downscaled predictions and observations of additional meteorological variables at equal time.

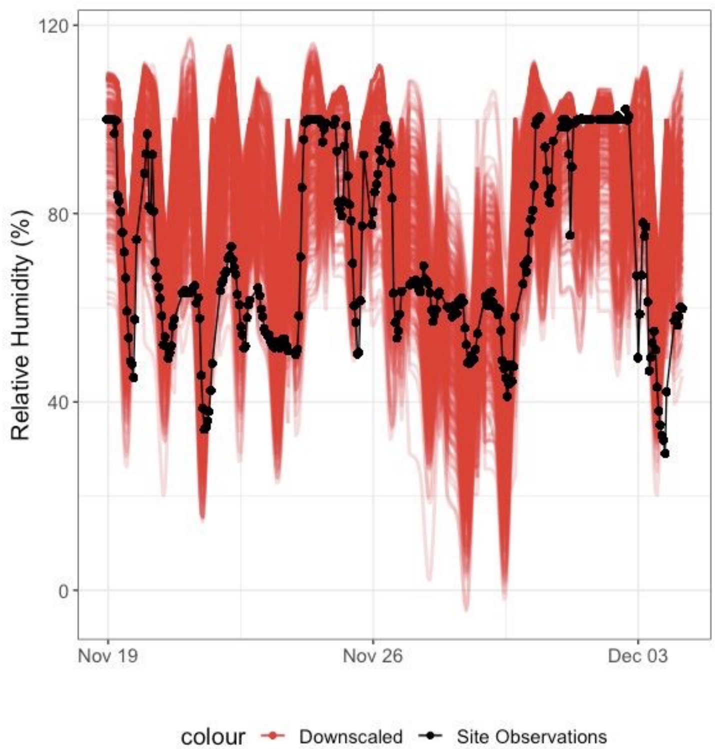

Figure 2. Observed relative humidity at 2 meters and 1-day predicted forecasts.

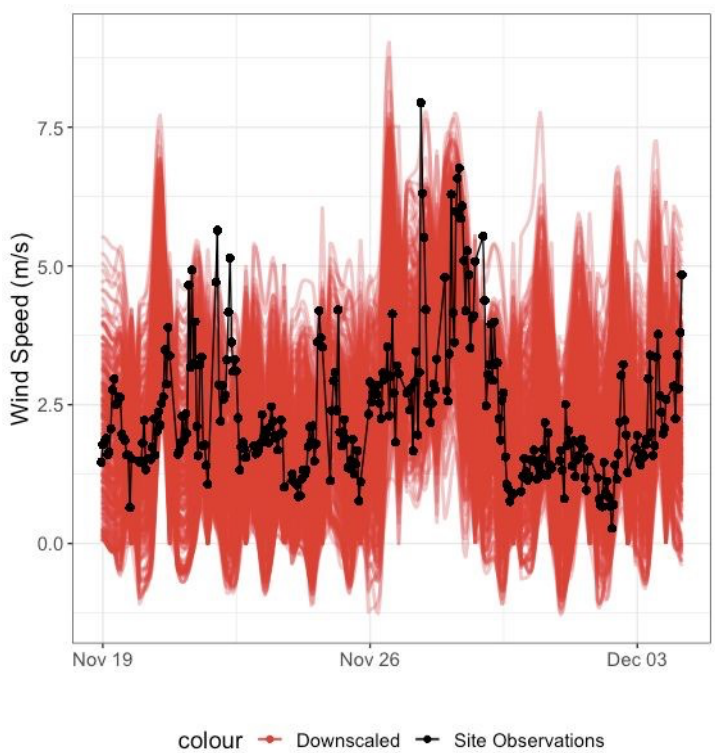

Figure 3. Observed wind speed at 10 meters and 1-day predicted forecasts.

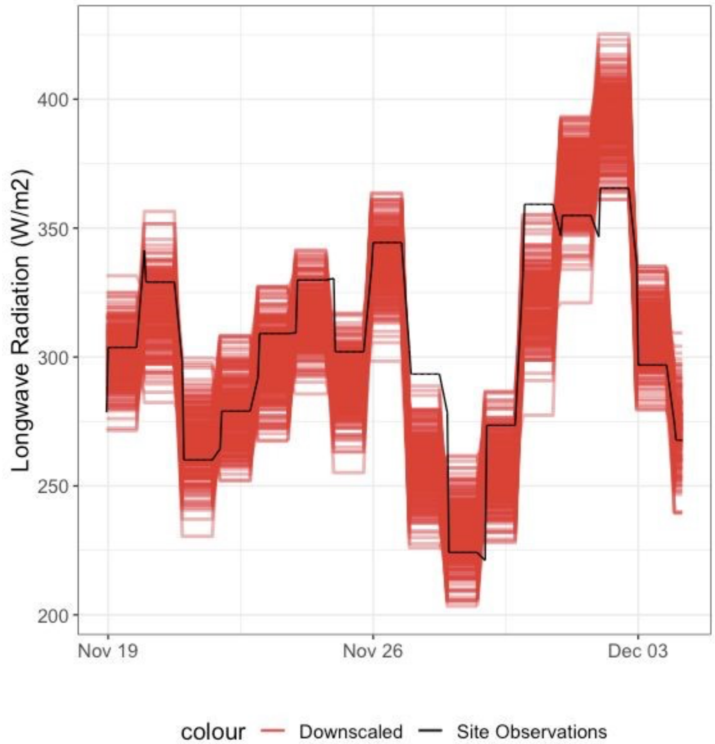

Figure 4. Observed longwave radiation flux and 1-day predicted forecasts.

Git Repository:
https://github.com/EcoDynForecast/NOAA_download_downscale