Solar Irradiance Covariance Modeling for Oahu, Hawaii

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Introduction

Solar irradiance measurements are highly correlated with the amount of energy produced by a grid of photovoltaic panels. Thus, reliable forecasting of irradiance will lead to reliable forecasting of energy output.
Utility-scaled solar plants are becoming more prominent. Modeling and forecasting methods of systems over various spatial and temporal resolutions are needed.
The spatio-temporal kriging forecaster [1]:

$$Z(s_0, t_0) = \mu(s_0, t_0) + \mathbf{c}(s_0, t_0)' \Sigma^{-1} (\mathbf{Z} - \mu)$$

where $\mathbf{Z} = (Z(s_1, t_1), \ldots, Z(s_n, t_n))'$ for n space-time coordinates, $\mu = E[\mathbf{Z}], \Sigma = cor(\mathbf{Z})$, and $\mathbf{c}(s_0, t_0) = cor(Z(s_0, t_0), \mathbf{Z})$.
Aryaputera et al. [2] used non-separable, direction dependent covariance models to forecast solar irradiance data.

- They used separate models fitted individually to time and space.
- The separate models were multiplied to make a separable covariance model.
- A non-separable model was used in which the separability parameterization of [3] was fitted.
- A directional model was used based on prior knowledge of wind for the day and location of their data set.

Purpose

For this project, we introduce a visual method that uses the correlation in the irradiance data to specify the directional covariance model.

Location Map

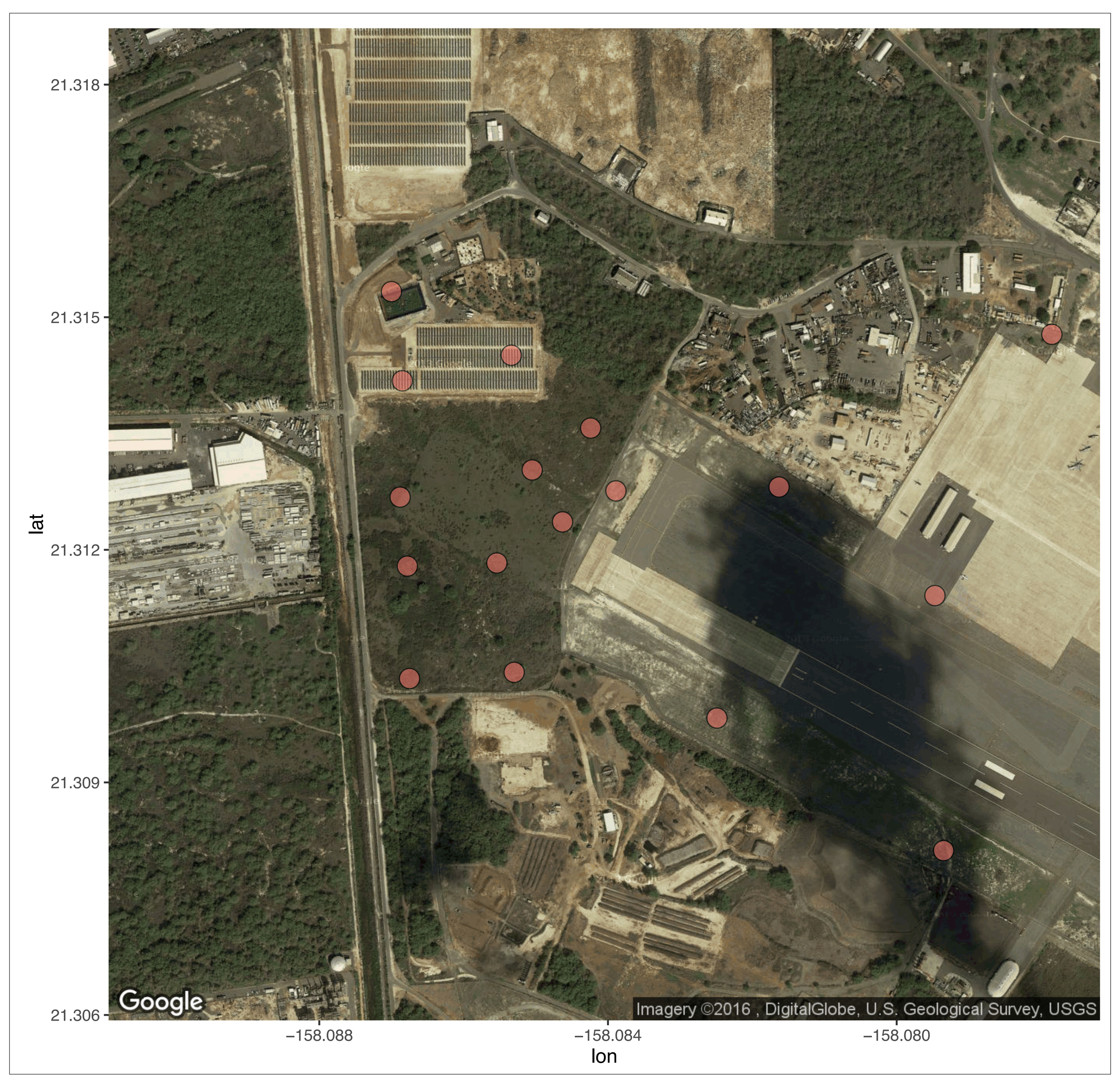

Figure: Oahu, Hawii

The data come from 17 sensors placed at the Oahu, HI, airport. The data were obtained from the National Renewable Energy Laboratory (NREL). Irradiance measurements were taken once a second for the entire day of August 5, 2012. The data were then averaged over every 30 seconds with the measurements taken at night removed. A clear sky model was used to detrend the data [4].

Separable and Fully Symmetric Models

- We first fit a separable covariance model by first fitting models to the spatial and time correlations separately:
- Exponential model for spatial:

$$\mathcal{C}_s(\boldsymbol{h}) = (1 - v)\exp(-c\|\boldsymbol{h}\|) + v\mathcal{I}_{\boldsymbol{h}=0},$$

- Cauchy model for time:

$$\mathcal{C}_t(u) = (a|u|^{2\alpha} + 1)^{-\tau}$$

- The separable covariance model is then

$$\mathcal{C}_{sep}(\boldsymbol{h}, u) = \mathcal{C}_s(\boldsymbol{h}) \times \mathcal{C}_t(u)$$

- The non-separable fully symmetric model is

$$\mathcal{C}_{FS}(\boldsymbol{h}; u) = \frac{1 - v}{(1 + a|u|^{2\alpha})} \times \left[\exp\left(-\frac{c\|\boldsymbol{h}\|}{(1 + a|u|^{2\alpha})^{\frac{\beta}{2}}}\right) + \frac{v}{1 - v}\mathcal{I}_{\boldsymbol{h}=0}\right]$$

- The values of v, c, a, and α are the same as for C_{sep}. Using these values, β is estimated which indicates the level of separability (0 = separable, 1 = non-separable).

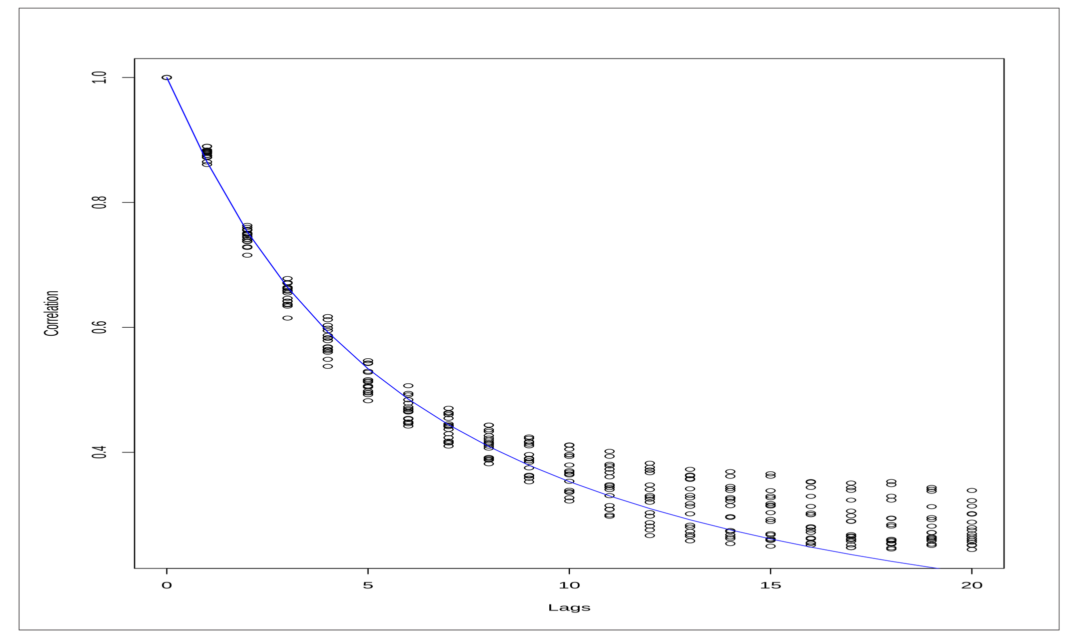

Figure: temporal-correlation

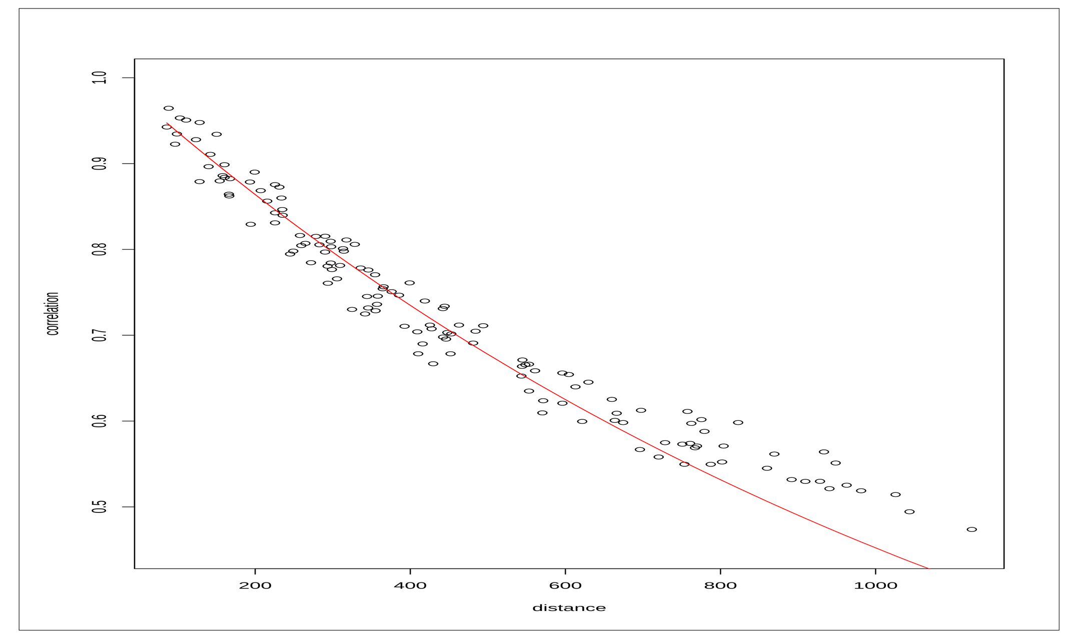

Figure: Spatial-correlation

Directional Models

- Calculate the directional distances for each pair of sensors: h_1 =along wind distance, h_2 =crosswind distance
- Find the differences between along wind correlation, $\text{corr}(Z(s_i, t - u), Z(s_j, t))$, and against wind correlation, $\text{corr}(Z(s_i, t), Z(s_j, t - u))$, for some time lag u for each pair of sensors $i \neq j$
- The difference correlation is modeled as

$$C_{diff}(h, u) = \left(I_{u>0} I_{h_1>0}\left[\beta_1^{(u)} h_1 + \beta_2^{(u)} h_2 + \beta_3^{(u)} h_1 h_2 + \beta_4^{(u)} h_1^2 + \beta_5^{(u)} h_2^2\right]\right)_+$$

- The directional correlation function is then

$$C_{dir}(h, u) = C_{FS}(h, u) + \alpha C_{diff}(h, u)$$

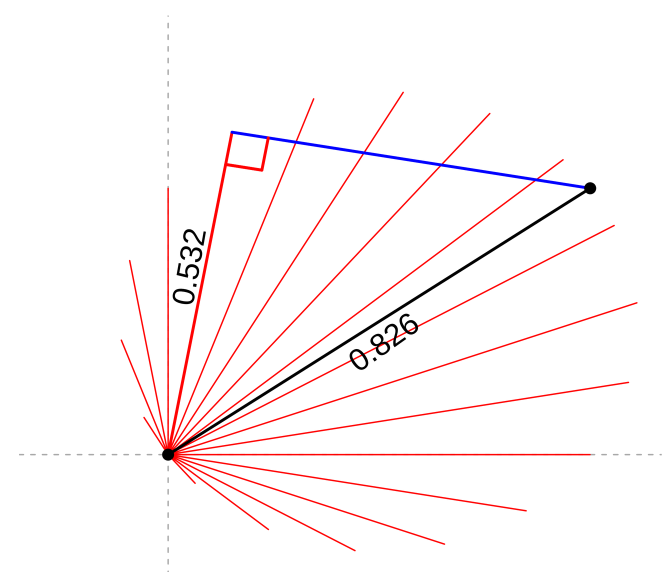

Figure: Example of directional distance

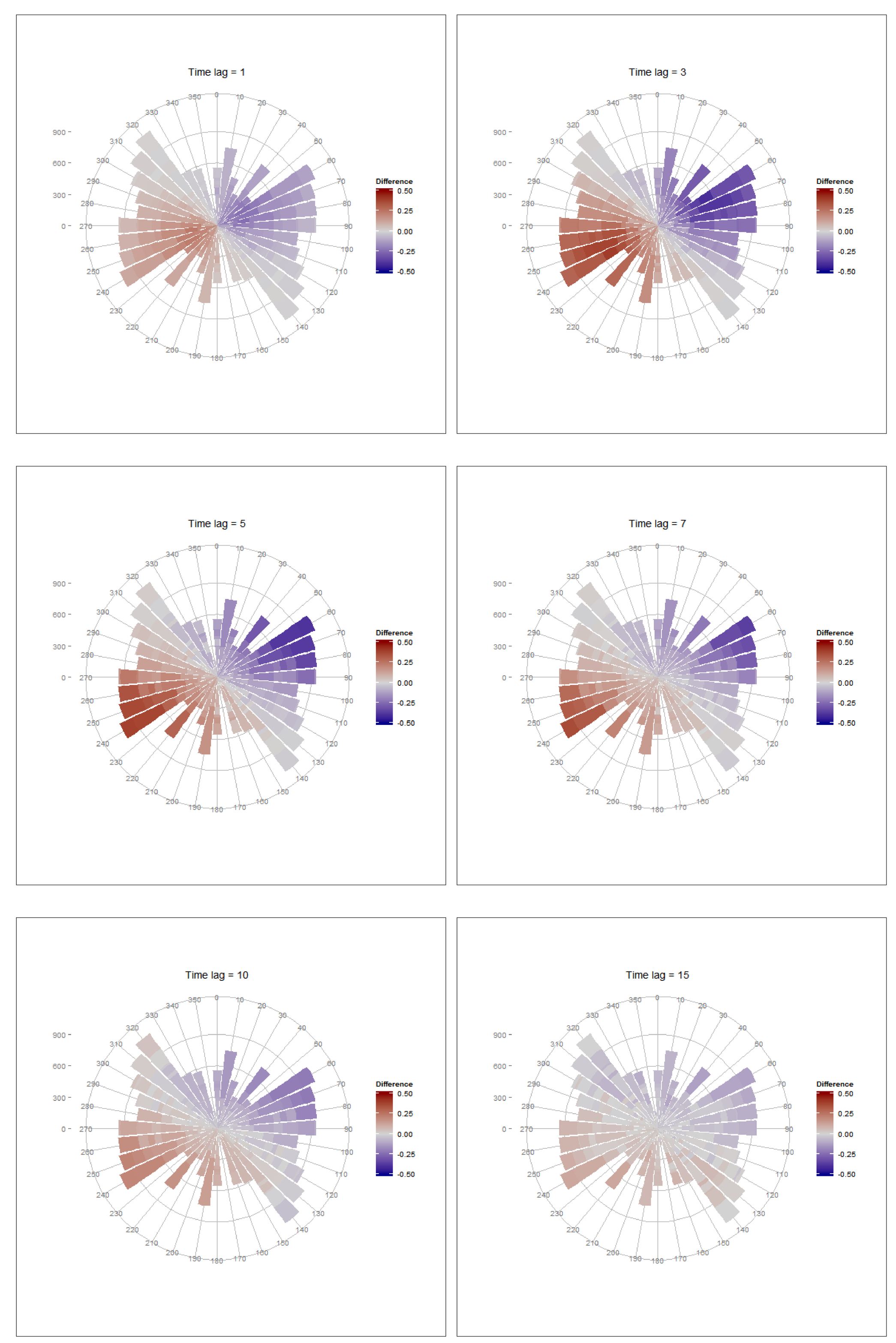

Figure: Directional correlation plots for the training data on Aug 5.

Result

- We used 50% training data. We utilized a moving window approach in which the previous 50% data was used to fit the model and then predict the next $u = 1, \ldots, 10$ time points.
- Weighted nonlinear least squares implemented with the `nls` function in `R` were used to fit the Cauchy and exponential models to the time and spatial correlations, respectively. We used inverse distance weights.
- When determining the direction, we only examined directional plots for the first 50% training data. For computational speed, we did not regenerate for each predicted time point. Thus, we are assuming the wind direction stays constant throughout the day.
- From the directional plots, we determined that the previous 5 time points (2 and half minutes) of data should be used to predict the next time point(s).
- In the figure below, we can see that the directional model results in the lowest root mean squared prediction error.

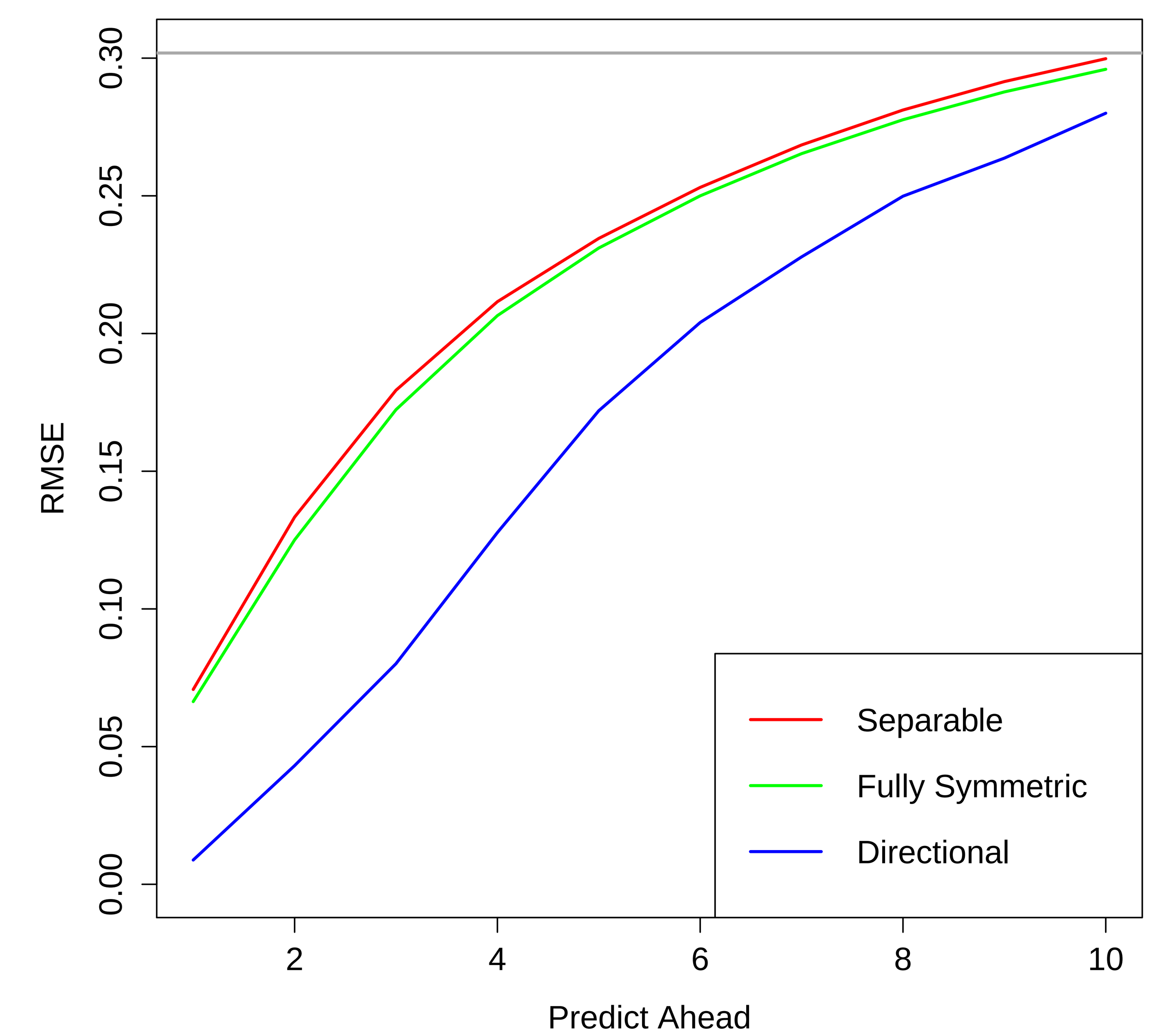

Figure: Root mean square prediction error for the three covariance models predicting $1, \ldots, 10$ time points ahead. The gray line represents the standard deviation of the testing data.

References

[1] Noel Cressie and Hsin-Cheng Huang. Classes of nonseparable, spatio-temporal stationary covariance functions. *Journal of the American Statistical Association*, 94(448):1330–1339, 1999.

[2] Aloysius W Aryaputera, Dazhi Yang, Lu Zhao, and Wilfred M Walsh. Very short-term irradiance forecasting at unobserved locations using spatio-temporal kriging. *Solar Energy*, 122:1266–1278, 2015.

[3] Tilmann Gneiting, Marc G Genton, and Peter Guttorp. Geostatistical space-time models, stationarity, separability, and full symmetry. *Monographs On Statistics and Applied Probability*, 107:151, 2006.

[4] Matthew J Reno, Clifford W Hansen, and Joshua S Stein. Global horizontal irradiance clear sky models: Implementation and analysis. *SANDIA report SAND2012-2389*, 2012.