Validation of a NN Weather Generator Methodology Based on North American Regional Reanalysis Historical Data

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Abstract

Stochastic weather generators (WGs) are finding increased adoption as a method to generate series of future climate data downscaled from the predictions of larger scale physical models, especially general circulation (GCM) and regional climate (RCM) models [1]. Statistical WGs are most commonly developed for single point applications. The WG developed by the RACC team seeks to improve upon this by examining the possibility of using downscaled GCM temperature (T) and precipitation (P) projections to draw upon finer scale North American Regional Reanalysis (NARR) records to generate regional weather data on a 32 km square grid over the Lake Champlain Basin region using a nearest neighbor approach.

We address the question of whether other weather variables contained in the NARR dataset such as pressure, relative humidity, shortwave solar radiation, cloud cover, and wind speed and direction as can be estimated based on T & P. The results in this poster show that sufficient correlation exists to reasonably predict the full range of NARR variables from this T & P combination.

Background

A stochastic WG is a statistical model, which draws upon records of past climate data to find similar conditions to those defined by a determined input variable. WGs do not create new data, nor do they predict weather per se. Instead, the input variables are used to select historical records with observed conditions that closely match the input variable. A subset of these records is then used to generate a simulated set of weather conditions that are a close statistical match. The NARR product is a physically modeled reanalysis regional weather conditions such as pressure, relative humidity, shortwave solar radiation, cloud cover and wind speed and direction which are bias corrected by historical station observations for the United States on a 32 km square grid.

Methods

To examine the predictive power of coupled T and P NARR resampling, a statistical binning system consisting of 14 P bins along the *x* axis and 14 T bins along the *y* axis was constructed [Fig. 1]. To ensure bin relationships reflect consistent changes in variable quantities, bins were divided into even increments as in Figure 1, with the exception of the last P bin, which includes records ranging from 13 to 234 mm of P.

Using WG algorithm parameters [Fig. 4], bins were used to extract a coincident sampling of NARR records across a full-year range. One way ANOVA tests were conducted for TP cells with more than 500 observations. *Results demonstrate significance of TP cell combinations on other NARR variables, with $p < 2.2 \times 10^{-16}$. Post-hoc Tukey HSD tests demonstrate that the majority of cells are unrelated at the $p < 0.05$ level. However, significant correlation ($p > .95$)* occurs between adjacent TP cells, expected due to the similarity of data in these cells. The effect is fleeting, with p values generally falling below $p = .95$ within a distance of 2 P cells. Though an expected effect, this relationship is difficult to communicate.

Perkins et al. [3] overcome this difficulty using a simple non-parametric method. The "Perkins Skill Score" determines the intersection between two probability density functions (PDFs), reporting the result as a percentage. Higher Perkins Scores indicate higher correlation between PDFs [Fig. 3]. Here, the Perkins Score is utilized to make pairwise comparisons between overall distributions of a weather variable from the T & P grid against the per-cell distribution of that variable. Perkins scores were analyzed based on distance between any grid cell (distance 0) and all other cells (maximum distance of 13). Distance between cells was determined by the Chebyshev "chessboard" metric [Fig. 2].

Figure 1: Bin Structure

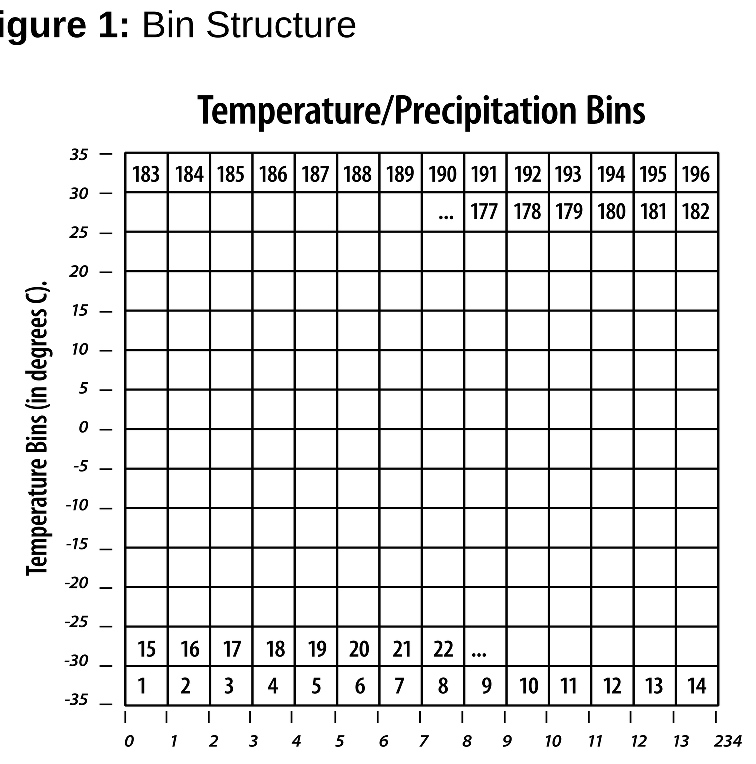


Figure 2: Chebyshev Distances

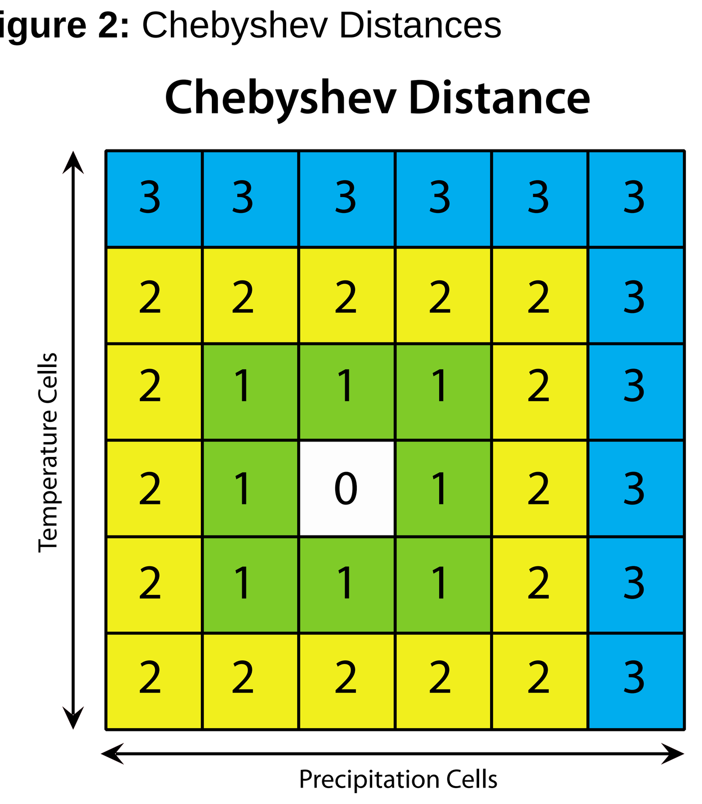


Figure 3: Perkins Scores

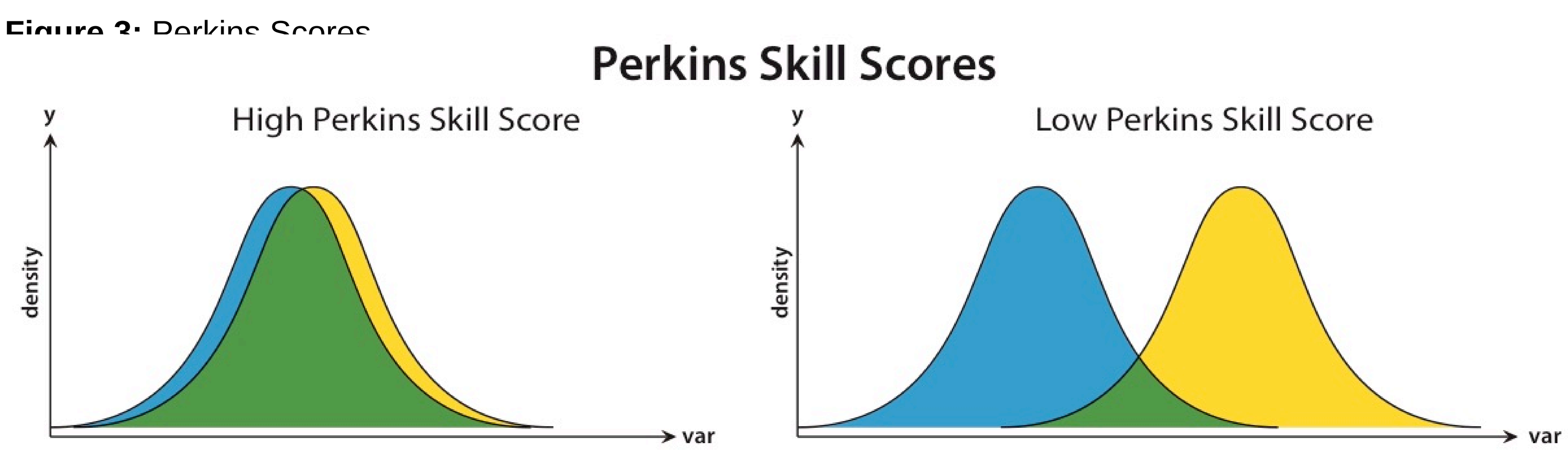
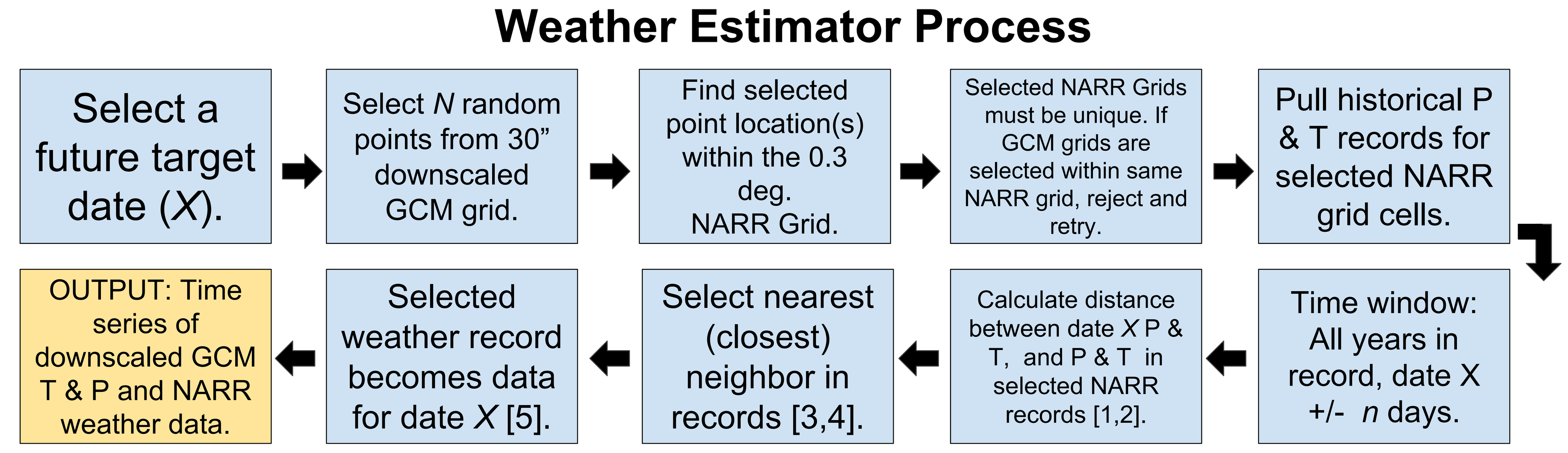


Figure 4: Weather Generator Process Flowchart

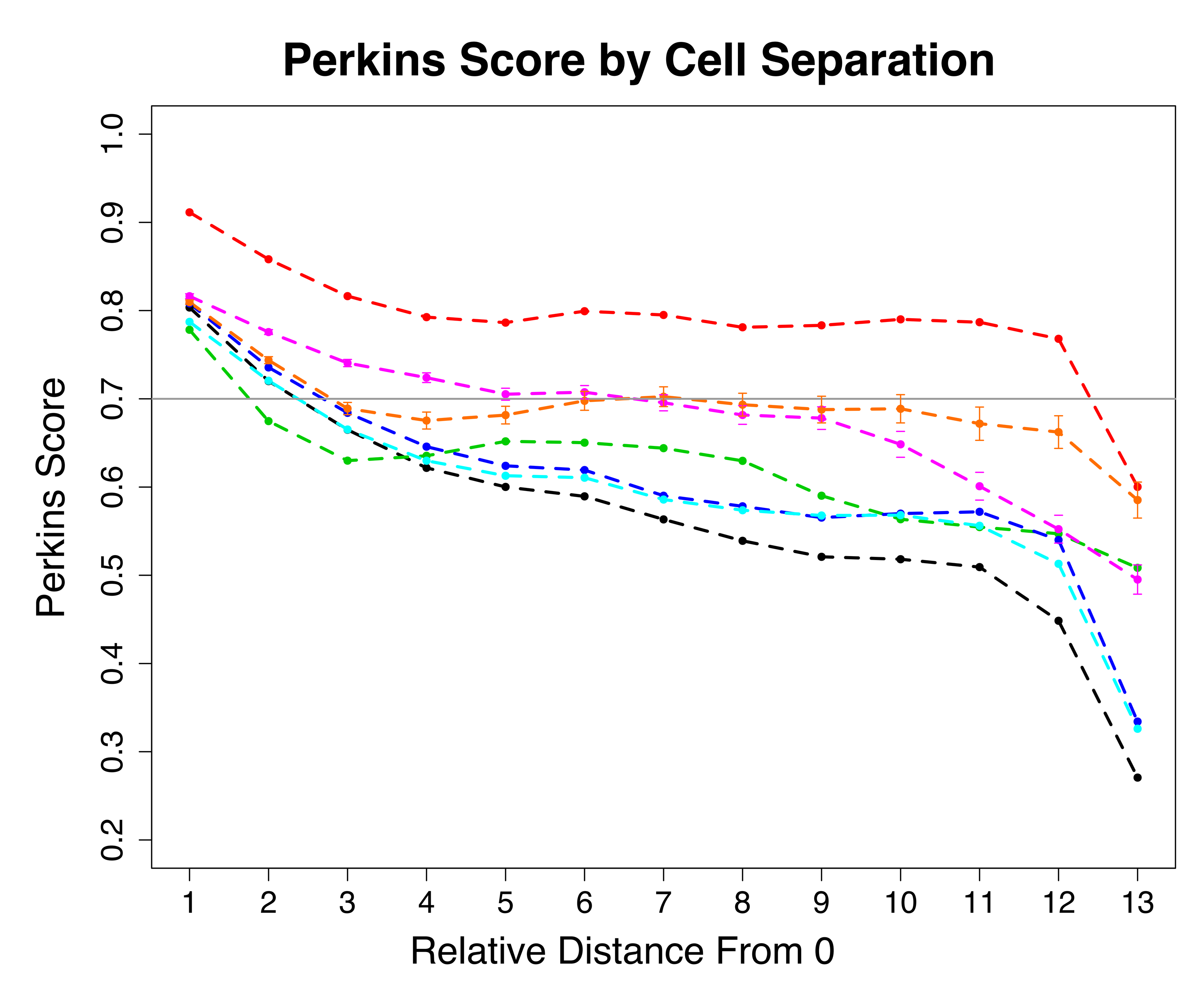


1. Sqrt: i=1:N(Sigma)(wT(Ttarget-TNARR)^2+wP(Ptarget-PNARR)^2)
2. We call this a "Multipoint Bivariate Weighted Euclidian Distance."
3. K is defined by user. If K=1, this is a simple NN Model. We're using K=1.
4. If K /= 1, NN is selected from a uniform distribution..
5. Series of and extreme weather events and extreme events are generated by the GCM. No Markov Chains, etc. are necessary.

Results

Results of the pairwise Perkins Skill test were determined in R, with plotted results in [Fig. 5]. Following Perkins et al [3], scores below .8 are considered significant, with scores below .6 extremely significant. These are plotted as solid horizontal lines. The mean of these two values, (.7) is often used to indicate significance, plotted as a dashed horizontal line. Bars are plotted as the standard error for each variable.

Figure 5: Analysis Results



Conclusions

Temperature and precipitation have significant predictive power for weather variables within a small Chebyshev distance when compared across a statistical grid over the NARR dataset, as defined in the discussion section.

- Within 2 cells distance, Perkins scores for all weather variables fall below the .8 threshold.
- Within 3 cells distance, 5 of 7 variables fall below the .7 threshold.
- An exception to the general pattern is barometric pressure, which plateaus just below the .8 threshold of significance.

It is suspected, but not investigated in this case, that the apparent weak performance in barometric pressure in relation to other weather variables is due to relative changes in pressure being more predictive of weather conditions than actual barometric pressure on any given date.

References

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