NARCCAP Model Validation for the Southeast United States

E D Kabela[1,2] and G J Carbone[1]

1 University of South Carolina, Dept. of Geography, Columbia, SC 29208
2 Oak Ridge National Laboratory, Global Nuclear Security Technology Div., Oak Ridge, TN 37831

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Introduction

Global climate models (GCMs) provide most projections of future climate change. But their coarse resolution limits their use in assessing regional climate change impacts on water resources, environmental quality, forest management, power plant operations, and many other fields. Such assessment requires translating global model output to more local scales. This research investigates dynamically downscaled regional climate model (RCM) output from the North American Regional Climate Change Assessment Program (NARCCAP) in the Southeast United States. Analysis includes assessments of GCM and RCM performance and skill in the region during a historical reference period (1970-1999), with explanations of sources and magnitude of individual model bias.

Three fundamental questions structure the research:

- How skillful are dynamically downscaled models in simulating minimum and maximum temperature and mean precipitation in a historical reference period (1970-1999) for the Southeast United States?
- Does downscaling improve projections at local scales? Is "value added" in downscaling?
- What are the magnitude of biases for each NARCCAP member (and variable) and what is the potential source of the bias?

Data and Methods

- 12km gridded observed dataset from 1970 to 1999 from the University of Washington (Maurer et al., 2002).
- 50km RCM historical (1970-1999) output from NARCCAP (Mearns et al., 2009).
- 32km North American Regional Reanalysis (Mesinger et al., 2006).
- Observed and RCM data remapped using nearest-neighbor algorithm from native coordinates and projections to WGC84 projection with 50km resolution.
- Daily grid point values extracted if within 0.5° of Alabama, Georgia, Mississippi, North Carolina, South Carolina, and Tennessee.

- **Four method used to quantify model skill:**
- **PDFs used to determine monthly model skill by calculating cumulative minimum value of two distributions of binned value, measuring common area between two PDFs (Perkins et al., 2007).**

$$S_{score} = \sum_{1}^{n} minimum(Z_m, Z_o)$$

n = number of bins, Z_m = frequency of values in a bin from model, Z_0 = frequency of values in a bin from observations. 0 = poor skill, 1 = high skill.

- **Calculate ratio between mean absolute error and mean absolute deviation about the observed mean (Willmott et al., 2011).**

$$d_r = \begin{cases} 1 - \dfrac{\sum_{i=1}^{n}|P_i - O_i|}{c\sum_{i=1}^{n}|O_i - \bar{O}|}, when \\ \sum_{i=1}^{n}|P_i - O_i| \le c\sum_{i=1}^{n}|O_i - \bar{O}| \\ \dfrac{c\sum_{i=1}^{n}|O_i - \bar{O}|}{\sum_{i=1}^{n}|P_i - O_i|} - 1, when \\ \sum_{i=1}^{n}|P_i - O_i| > c\sum_{i=1}^{n}|O_i - \bar{O}| \end{cases}$$

n = number of values, P_i = predicted values, O_i = observed values, $\bar{O}$ = observed mean. -1 = poor skill, 1 = high skill.

- **Root Mean Square Error (RMSE)**

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$$

- **Mean Absolute Error (MAE)**

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j|$$

n = number of bins, y_j = observed values, $\hat{y}_j$ = modeled values

Results – Value Added

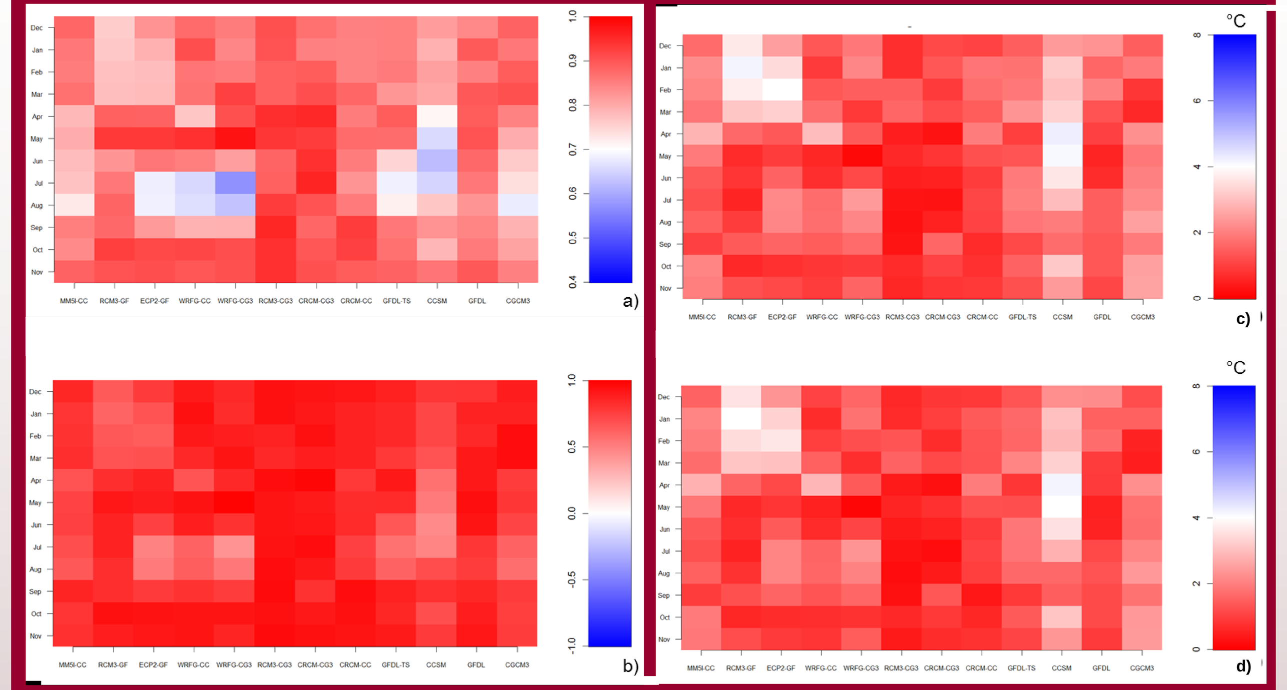

Figure 1: Hovmöller diagram of minimum temperature Perkins skill score (a), Willmott's index of agreement (b), RMSE (c), and MAE (d) for the east sub-region.

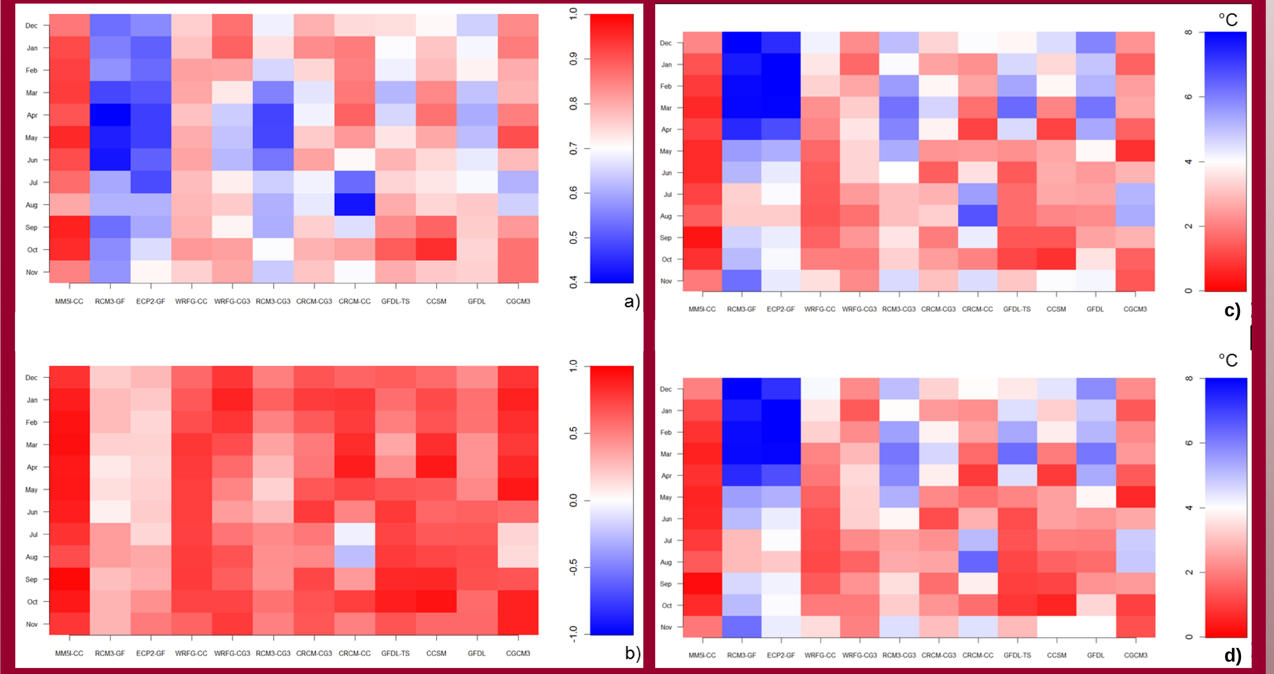

Figure 2: Hovmöller diagram of maximum temperature Perkins skill score (a), Willmott's index of agreement (b), RMSE (c), and MAE (d) for the east sub-region.

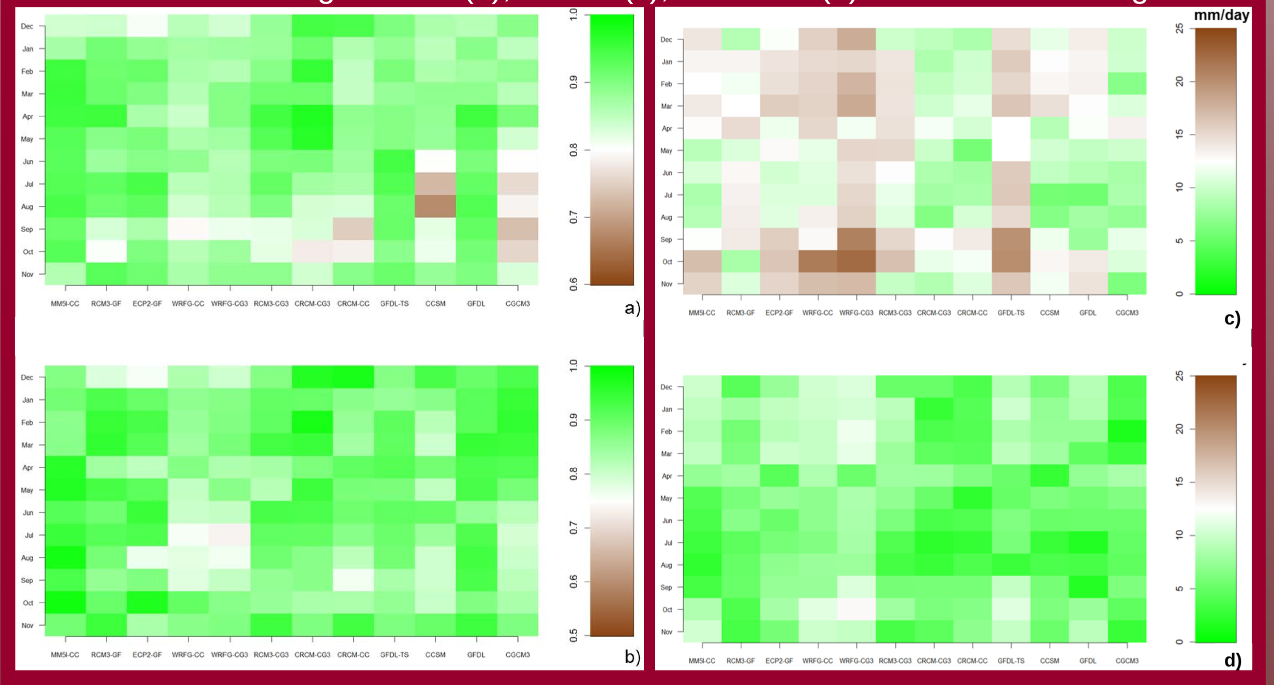

Figure 3: Hovmöller diagram of mean precipitation Perkins skill score (a), Willmott's index of agreement (b), RMSE (c), and MAE (d) for the east sub-region.

Model Key:

MM5I-CC	= MM5I-CCSM	CRCM-CG3	= CRCM-CGCM3
RCM3-GF	= RCM3-GFDL	CRCM-CC	= CRCM-CCSM
ECP2-GF	= ECP2-GFDL	GFDL-TS	= GFDL-Timeslice
WRFG-CC	= WRFG-CCSM	CCSM	= CCSM GCM
WRFG-CG3	= WRFG-CGCM3	GFDL	= GFDL GCM
RCM3-CG3	= RCM3-CGCM3	CGCM3	= CGCM3 GCM

Results – Value Added

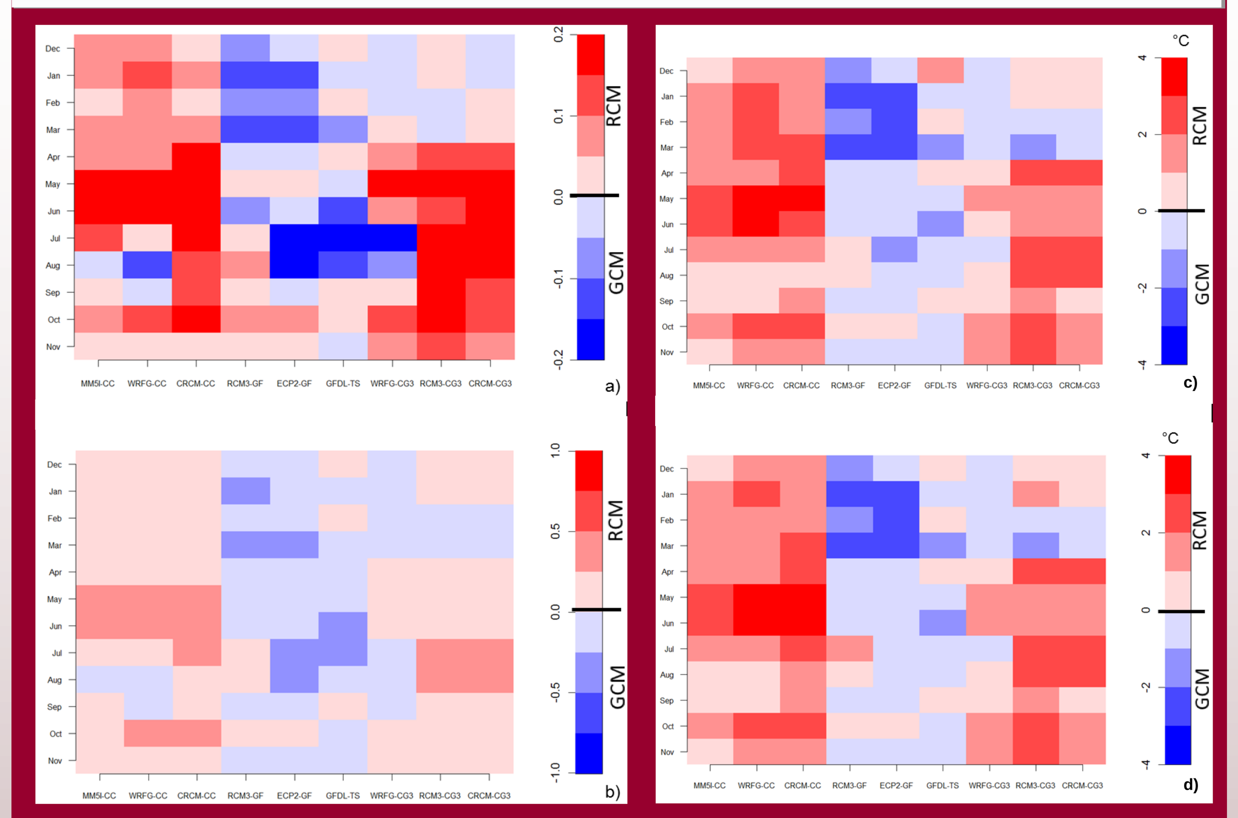

Figure 4: Value added for minimum temperature Perkins skill score (a), Willmott's index of agreement (b), MAE (c), and RMSE (d) for the east sub-region.

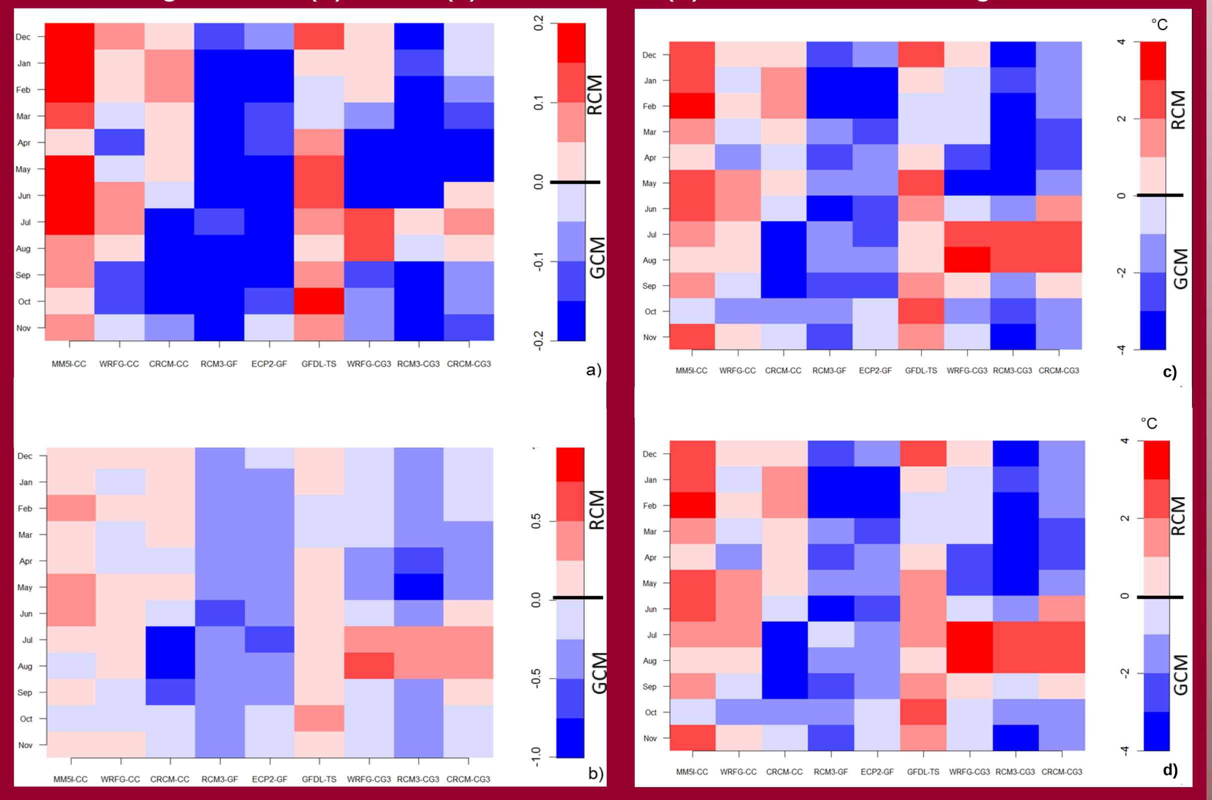

Figure 5: Value added for maximum temperature Perkins skill score (a), Willmott's index of agreement (b), MAE (c), and RMSE (d) for the east sub-region.

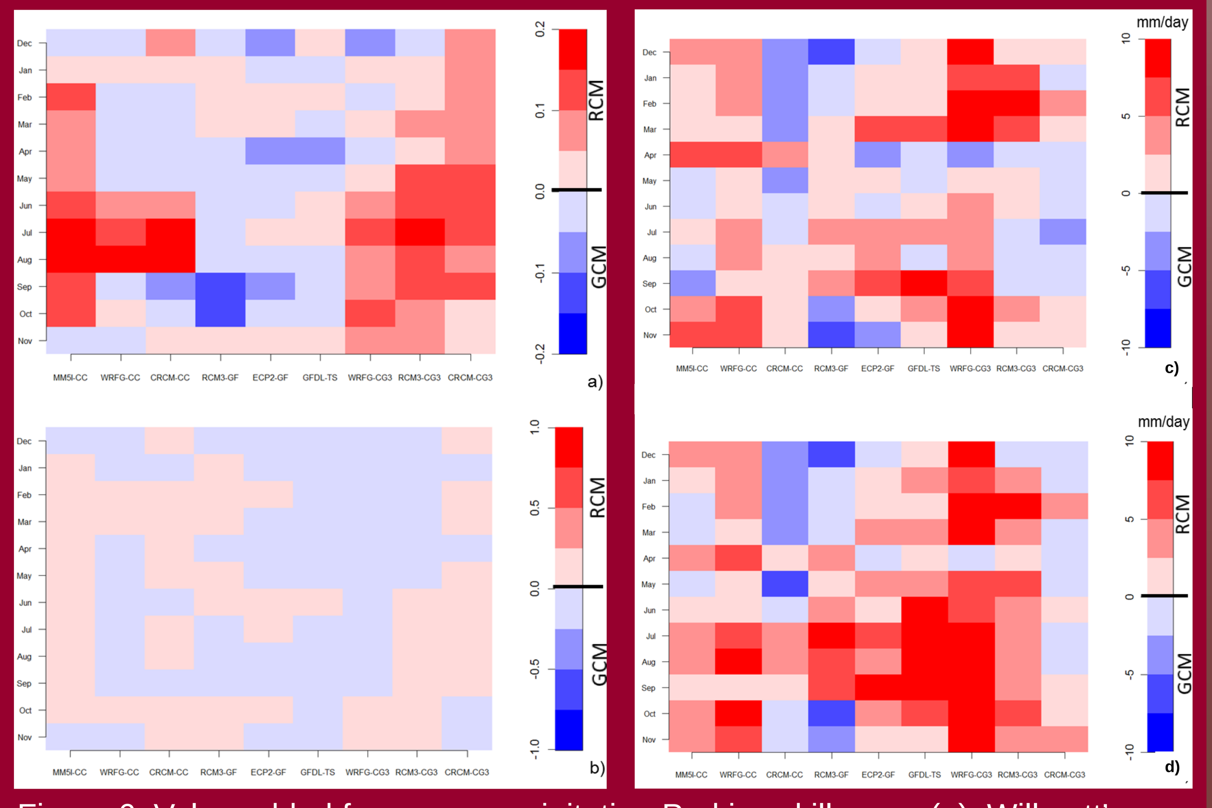

Figure 6: Value added for mean precipitation Perkins skill score (a), Willmott's index of agreement (b), MAE (c), and RMSE (d) for the east sub-region.

Results – Model Bias

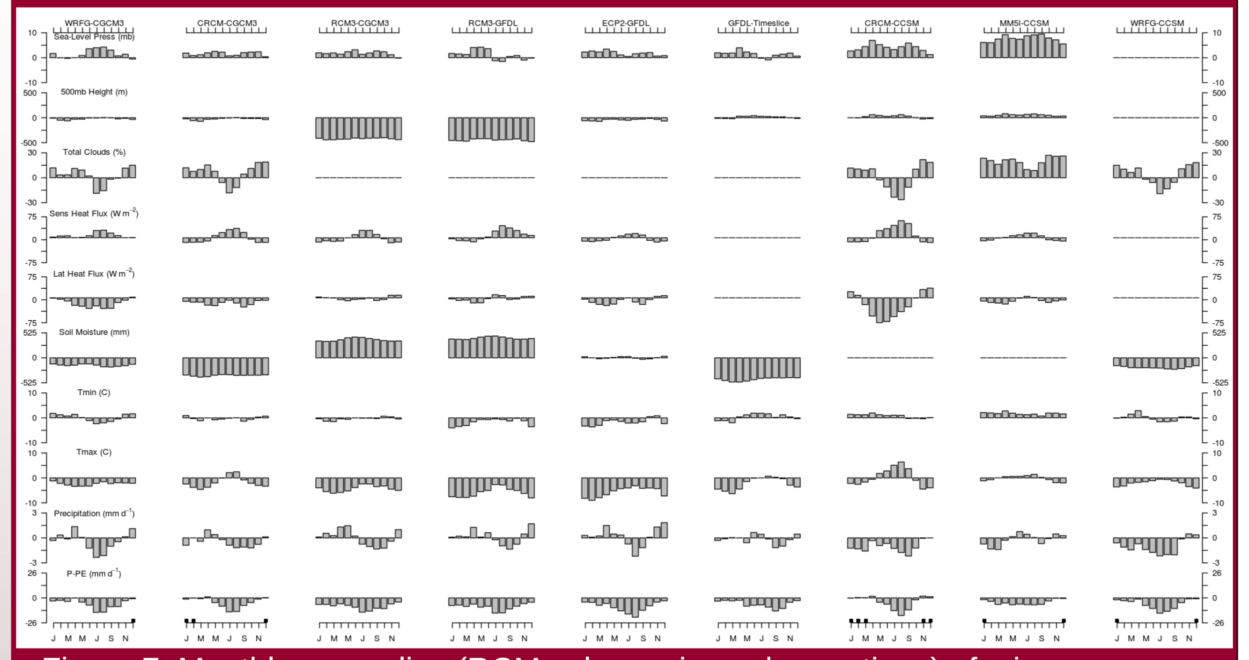

Figure 7: Monthly anomalies (RCM values minus observations) of micro-, meso-, and synoptic-scale components for grid points from the east sub-region. Black boxes on the precipitation minus potential evapotranspiration (P-PE) histograms represent a model-predicted surplus of moisture for the respective month (P-PE before subtracting from observations). Each histogram begins with the month of January and ends with the month of December (x-axis of each histogram).

Conclusions

- All models relatively skillful in reproducing daily minimum temperature trends for both sub-regions, less overall skill observed for maximum temperature.
- WRFG RCMs, ECP2-GFDL, and GFDL-timeslice show degradation in skill during summer months while RCM3-GFDL and ECP2-GFDL exhibit degradation in winter (min temperature). RCM3- and ECP2-GFDL exhibit very low skill across all months (max temperature). Most consistently skillful models across all months are RCM3- and CRCM-CGCM3, and MM5I-CCSM.
- GFDL-timeslice has higher skill and more value added than either RCM run with GFDL LBCs.
- Mean precipitation model skill (regardless of sub-region) highly dependent on skill metric.
- Value added by individual ensemble members highly dependent on skill metric and month . For temperature, RCMs driven by the CCSM GCM added most value. Those driven by GFDL added least value (with exception of GFDL-timeslice). For precipitation, WRFG- and RCM3-CGCM3 most consistently added value across all months with MM5I-CCSM adding positive value for least nine months out of year. Models adding least value were CRCM-CCSM and GFDL-timeslice.
- Comparison of climatological variables at micro-, meso-, and synoptic-scales revealed systematic biases for those models which exhibited less skill.

Acknowledgements

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Contact Information: Erik D. Kabela, kabelaed@ornl.gov, 1 Bethyl Valley Road, Oak Ridge, TN 37831

Dr. Greg J. Carbone, greg.carbone@sc.edu
Callcott Building, 709 Bull St. Columbia, SC 29208