NARCCAP Model Validation for the Southeast United States

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Overview

• Research Questions
• Data and Methods
  – Skill Assessment
  – Value Added
  – Bias
• Key Findings
Research Questions

• How skillful are NARCCAP models in simulating daily minimum and maximum temperature and mean precipitation in a historical reference period (1970-1999) for the Southeast United States?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?
  – i.e., is “value added” in downscaling?

• What are the biases for each NARCCAP member (and variable)
  – What is the potential source of the bias?
Data and Methods - Data

- 9 NARCCAP members
  - MM5I-CCSM, RCM3-GFDL, RCM3-CGCM3, ECP2-GFDL, WRF-GCCSM, WRF-CGCM3, CRCM-CGCM3, CRCM-CCSM, GFDL-Timeslice

- Observed dataset: Maurer gridded dataset
  - 12 km resolution, daily temporal resolution
  - Daily min, max temperature and mean precipitation

- North American Regional Reanalysis (NARR)
  - Soil moisture, latent and sensible heat flux, total cloud cover, 500mb height, and sea-level pressure
Data and Methods - Methods

- Re-grid to 50km, simple lat/long projection (nearest neighbors)
- 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)
- Calculate ratio between mean absolute error and mean absolute error of observations about the observed mean (Willmott et al., 2011)
- RMSE and MAE
Data and Methods - Methods

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$$S_{score} = \sum_{1}^{n} \min(Z_m, Z_0),$$

$n =$ number of bins, $Z_m =$ frequency of values in a bin from model, $Z_o =$ frequency of values in a bin from observations.

$0 =$ poor skill, $1 =$ high skill.
Data and Methods - Methods

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\[
d_r = \begin{cases} 
1 - \frac{\sum_{i=1}^{n}|P_i - O_i|}{c \sum_{i=1}^{n}|O_i - \bar{O}|}, & \text{when} \\
\sum_{i=1}^{n}|P_i - O_i| \leq c \sum_{i=1}^{n}|O_i - \bar{O}| \\
\frac{c \sum_{i=1}^{n}|O_i - \bar{O}|}{\sum_{i=1}^{n}|P_i - O_i|} - 1, & \text{when} \\
\sum_{i=1}^{n}|P_i - O_i| > c \sum_{i=1}^{n}|O_i - \bar{O}| 
\end{cases}
\]

\( n = \) number of values, \( P_i = \) predicted values, \( O_i = \) observed values, \( \bar{O} = \) observed mean.
-1 = poor skill, 1 = high skill.
Data and Methods - Methods

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• RMSE and MAE

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

\[
\text{MAE} = \frac{1}{n} \sum_{j=1}^{n} |y_j - \hat{y}_j|
\]
Model Skill – Min. Temp

RMSE

MAE
Model Skill – Max. Temp

Perkins

Willmott

RMSE

MAE

MM5I  RCM3  ECP2  WRFG  WRFG  RCM3  CRCM  CRCM  CCSM  GFDL  CGCM3
CCSM  GFDL  CGCM3  RCM3  CGCM3  CCSM  GFDL  CCSM  GFDL  CGCM3

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Value Added – Min. Temp

Perkins

MAE

Willmott

RMSE
Value Added – Mean Precip

Perkins

MAE

Willmott

RMSE

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Key Findings

• All models relatively skillful in reproducing daily minimum temperature 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
  – RCM3-GFDL and ECP2-GFDL exhibit degradation in winter (min temp)
  – RCM3-GFDL and ECP2-GFDL exhibit very low skill across all months (max temp).

• Most consistently skillful (temp) are RCM3- and CRCM-CGCM3, and MM5I-CCSM.

• GFDL-Timeslice has higher skill and more value added than either RCM run with GFDL lateral boundary conditions (LBCs)

• Most models prove relatively skillful with respect to precipitation
Key Findings

• Value added by individual ensemble members dependent on skill metric and month
  – Temp: RCMs with CCSM LBCs added most value; RCMs with GFDL LBCs added least (with exception of GFDL-Timeslice)
  – Precip: WRFG- and RCM3-CGCM3, and MM5I-CCSM adding most value; CRCM-CCSM and GFDL-Timeslice offer least value added

• Comparison of climatological variables at micro-, meso-, and synoptic-scales reveal systematic biases for those models which exhibited less skill
Acknowledgements

• This research was funded by award number NA06OAR4310007 from the NOAA Climate Program Office to the Carolina Integrated Sciences and Assessments.

• A special thank you to my advisor, Greg Carbone, and my committee, Susan Cutter, Brian Habing, and Cary Mock.
Questions??
References
