Downscaling Climate Change Information for Water Resource and Agricultural Interests in the Southeast United States

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Introduction

This work 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 assessment of RCM performance in the region during the historical period, with explanations of model bias, as well as quantification of uncertainty in future scenarios that results from differing models and downscaling methods. The focus will be on monthly temperature and precipitation changes across the region.

Data Source and Methods

- 12km gridded observed dataset from 1970 to 1999 from the University of Washington (Maurer et al., 2002).
- 50km RCM historical (1970-1999) and future (2041-2070) output from NARCCAP (Mearns et al., 2009).
- Gridded 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.
- Probability density functions (PDFs) created for observed dataset and each RCM in historical period using extracted data.
- PDFs used to determine monthly model skill by calculating cumulative minimum value of two distributions of a binned value, measuring the common area between two PDFs (Perkins et al., 2007).

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

where n is the number of bins used to calculate PDF, Z_m is the frequency of values in a given bin from the model, and Z_o is the frequency of values in a given bin from the observed data.

- Skill based on scale from zero (low skill) to one (high skill).
- Skill score used to calculate weighted average for future precipitation and temperature change.

Results

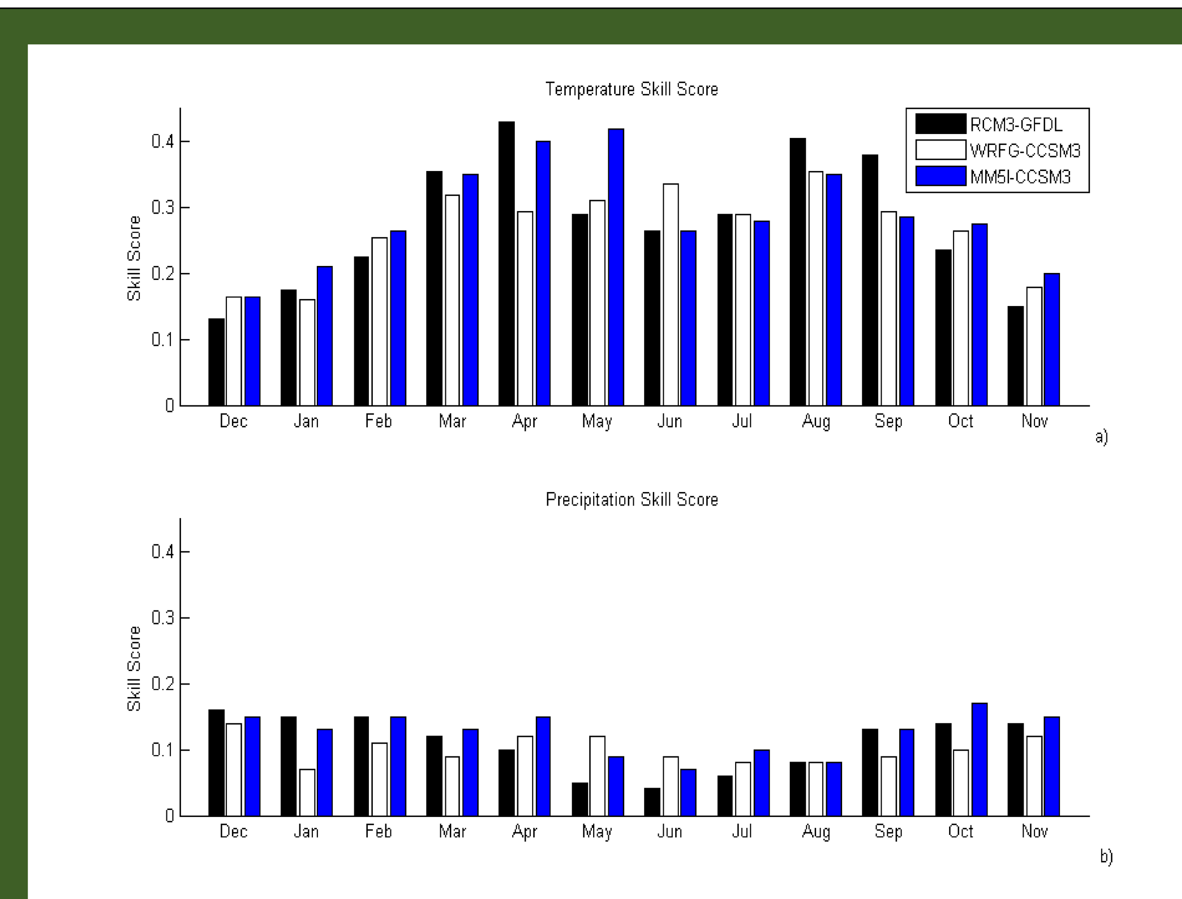

Figure 1: Monthly skill scores for RCM3-GFDL, WRFG-CCSM3, and MM5I-CCSM3 regional climate models (a) temperature and (b) precipitation for the period 1970-1999 for the Southeast U.S.

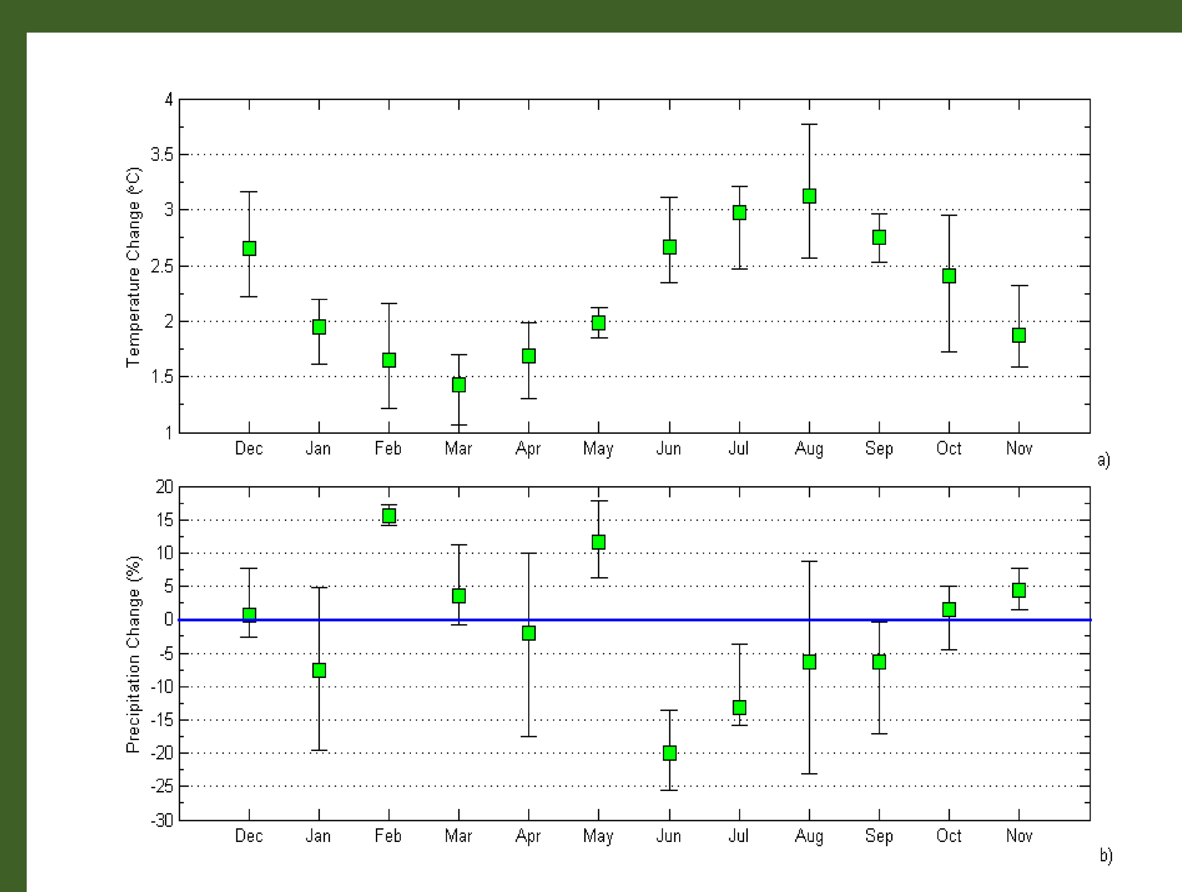

Figure 2: Projected (a) temperature and (b) precipitation change for the Southeast U.S. from 1970-1999 to 2041-2070. Green boxes represent weighted average of three RCMs. Error bars represent lowest and highest individual model mean.

Results

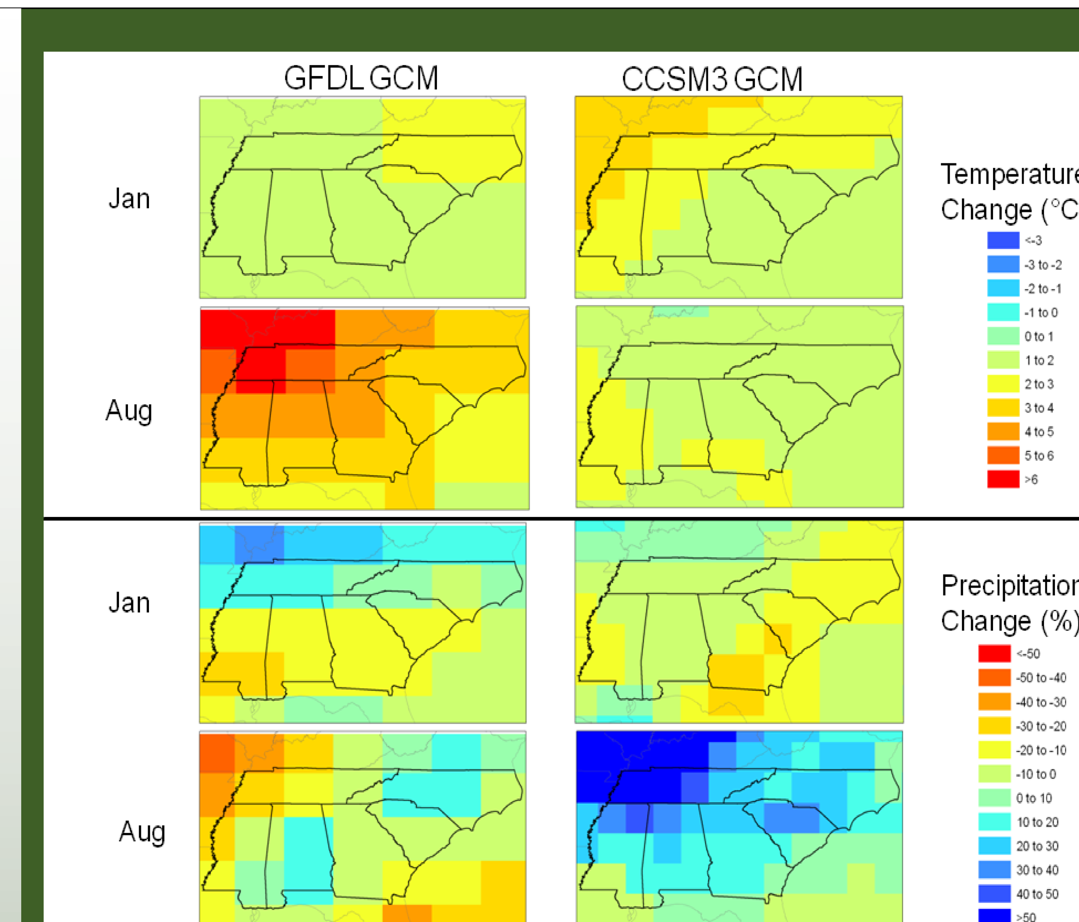

Figure 3: January and August temperature and precipitation change projections from two GCMs (100km resolution) used in NARCCAP. These were used as boundary conditions for RCMs in Figure 4 for the period 1970-1999 to 2041-2070.

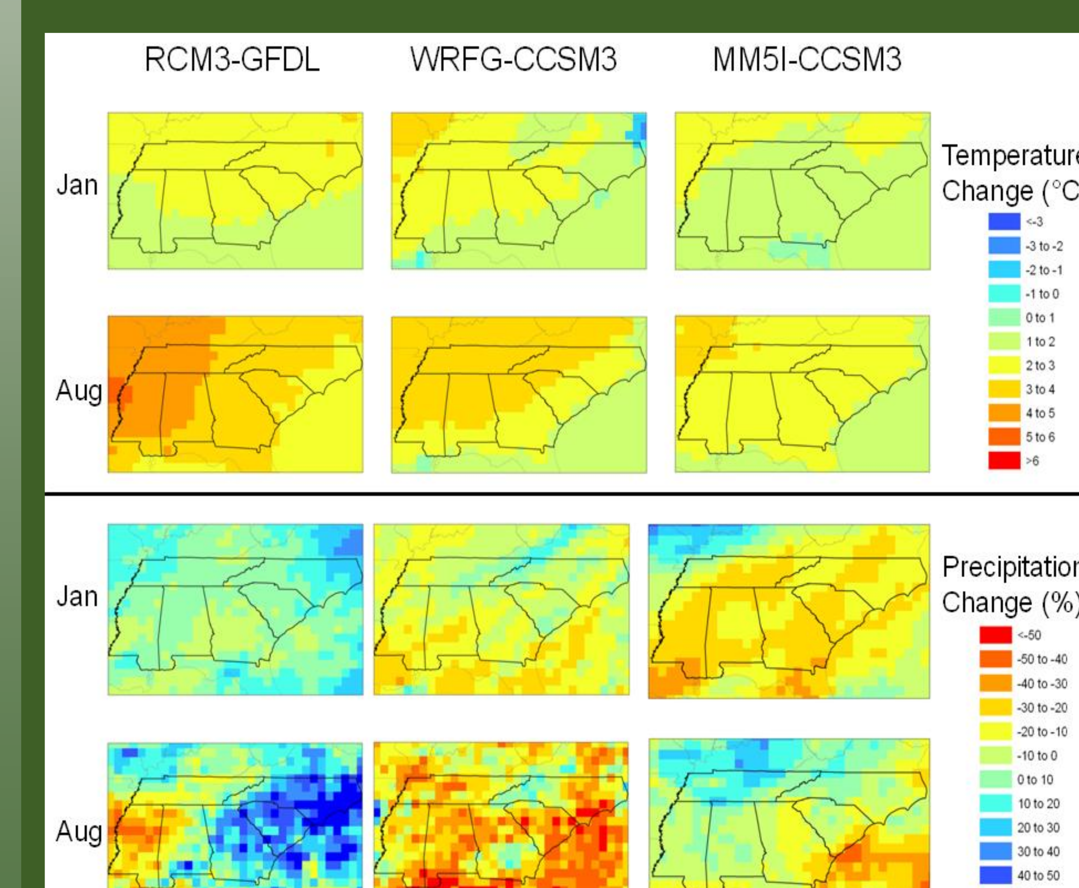

Figure 4: January and August temperature and precipitation change projections from three NARCCAP RCMs for the period 1970-1999 to 2041-2070.

Conclusions

- Largest amount of uncertainty in regional climate change projections is derived from choice of GCM (Deque et al., 2007; Jacob et al., 2007) with RCM choice accounting for the second largest amount of uncertainty (Giorgi, 2006).
- RCMs show some skill in modeling historical temperature, especially during the warm months.
- RCMs show little skill in modeling cold season historical temperature.
- Precipitation skill scores are low for all months. Highest model skill occurs in winter, early spring, and late fall. Model skill lowest in late spring, summer, and early fall.
- MM5I-CCSM3 RCM shows highest overall skill with WRFG-CCSM3 RCM showing least skill.
- Temperature change projections indicate warming trend for each month with highest increases in summer, early fall, and December (over 2.5°C warming). Projections are lowest in late winter and early to mid spring (less than 1.75°C warming).
- Wetter conditions projected for February through May (7.3% average increase) with drier conditions projected for June through September (11.5% average decrease).
- Spatial patterns of January and August temperature change similar between RCM and driving GCM.
- Spatial patterns of January precipitation similar between RCM and driving GCM, however, August precipitation change projections show disconnect between RCM and GCM.

Acknowledgements

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