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Comparison of Dynamically and Statistically Downscaled Seasonal Climate Forecasts for the Cold Season over the United States

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ABSTRACT

This study compares two approaches, dynamical and statistical downscaling, for their potential to improve regional seasonal forecasts for the United States (U.S.) during the cold season. In the Multi-RCM Ensemble Downscaling (MRED) project, seven regional climate models (RCMs) are used to dynamically downscale the Climate Forecast System (CFS) seasonal prediction over the conterminous U.S. out to 5 months for the period of 1982–2003. The simulations cover December to April of next year with 10 ensemble members from each RCM with different initial and boundary conditions for the corresponding ensemble members. These dynamically downscaled forecasts of precipitation (P) and surface air temperature (T) are compared with statistically downscaled forecasts produced by two bias correction methods of Bias Correction and Spatial Disaggregation (BCSD) and Bayesian merging applied to both the CFS and RCM forecasts.

The RCMs generate finer-scale features that are missing from CFS in terms of both climatology and anomaly from the long-term mean. However, forecast skill of the downscaled P and T can vary for different metrics used in the cross validation. In terms of temporal anomaly correlation (AC), it is found that RCMs and statistical downscaling methods generally are somewhat higher than CFS, especially in the Northwest and North Central regions. For this skill measure, some RCMs can even outperform the multi-model ensemble or combined dynamical-statistical methods. For skill measured by spatial correlation, RCMs and statistical downscaling also provide additional values in addition to CFS. The Bayesian method performs poorly for AC because of the large ensemble spread in the forecasts. Using RMSE as the metrics (Fig. 1), we find that a couple of RCMs can reduce forecast errors compared to CFS, but some RCMs have higher RMSE due to the overprediction of precipitation in the Northwest and Northern California. However, the RCMs combined with

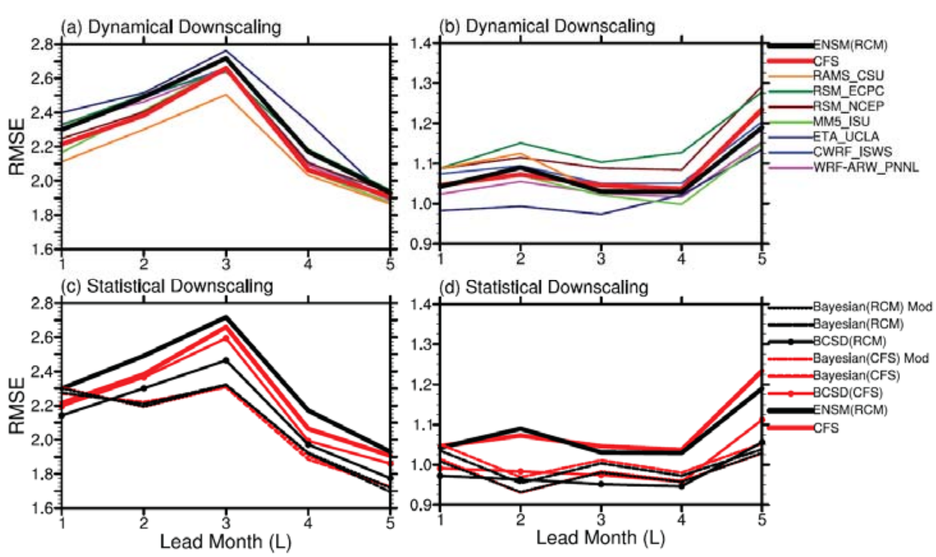

Fig. 1 Root Mean Squared Error (RMSE) of Surface air temperature (a and c) and precipitation (b and d) averaged over the contiguous U.S. RMSE of all the regional climate models are in the top panels (a and b) and statical downscaling methods in the bottom (c and d). Y axis in the left column (a and c) is deg C and that in the right column (b and d) is in mm/day.

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statistical bias correction stand out clearly. At the first-month lead, simple BCSD of all seven RCMs do surprisingly well. At the longer leads, the Bayesian merging applied to either CFS or RCMs does a good job. Improvement of forecast skill can be found over the mountainous regions, especially the western U.S. during the winter season.

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