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Comparison of regional downscaling methods: Dynamic downscaling using MRED vs. statistical methods

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37th NOAA Climate Diagnostics and Prediction Workshop Ft. Collins, CO Oct. 22 – Oct. 25, 2012

Why do we need 'Regional Downscaling'?





- CFSv1 is about 200km in spatial resolution.
 - Not possible to use in regional application, such as wet/dry condition over the Colorado River basin.
 - CFSv2 is about 100km, which is still not enough for regional application.

Two approaches in Regional Downscaling



- Dynamic Downscaling: Using high-resolution limited area model forced by typically low-resolution global forecast model output.
 - MRED (Multi-RCM Ensemble Downscaling): Community effort to produce 26 years of winter (December – April) reforecast from NOAA CFS global seasonal forecast model.
 - ~32km resolution
 - 1982 2003
 - Totally 7 RCMs are used: WRF-ARW, MM5, CWRF, ETA, RSM_NCEP, RSM_ECPC, RAMS
- Statistical Downscaling: Using historical relationship between forecast and high-resolution observation.
 - BCSD (Bias Correction and Spatial Disaggregation)
 - Bayesian merging

MRED: dynamic downscaling



- Results for boreal winter forecast when orography precipitation plays an important role in the Western US.
- Demonstrate how much extra value can be added using multi-model downscaling of global seasonal forecast for hydrometeorological application (Precipitation & Sfc. Air temperature).
- Compare this dynamic downscaling with the sets of statistical methods.



Statistical downscaling methods



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- **BCSD:** Probability mapping based on distributions
 - obtain probability distribution PDFs for A (coarse T62 fcsts) and A(fine, obs)
 - From A' (coarse) get percentile based on PDF (coarse)
 - assume the same percentile for the fine grid and work backward based on the PDF fine get A' fine (anomaly)
 - If normally distributed, time ratio of std.
 - Ref Wood et al (U. Washington) 2002,2006) S(fine) S(coarse)

$$A'(fine) = A'(coarse)$$
*

- Bayesian merging: Using Bayes' theorem to update forecast
 - Based on (1) ensemble spread and (2) historical skill
 - Ref: Luo et al. (2007), Luo and Wood (2008)



RCM simulated rainfall climatology



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However, bias still exists and calibration/bias correction is required.

RCM simulated precipitation anomalies



- Precipitation anomalies simulated by RCMs tend to have similar structure as that by CFS.
- Once again, bias correction or Calibration is needed.



Anomaly correlation (Precipitation)





Anomaly Correlation: computed at each grid point in the hindcast period of 1982 – 2003.

Area show higher correlation (Precipitation)



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Spatial Correlation and RMSE









- It is clear that RCMs do reproduce similar, but generally improved, precipitation (P) and surface air temperature (T) anomaly compared to CFS. However, the improvement is highly dependent on location and forecast lead time.
- In other words, at some locations and certain lead months, RCMs do add values but certainly not always and not everywhere.

Probabilistic view of RCM skill





- Reliability diagram
 - All of the forecasts either from CFS or RCMs are overconfident and have little distinction.
 - For above-normal precipitation forecast, RCMs do have more reliability than CFS predicting those events occurring more frequently, and vice versa.
 - However, this relationship changes for below-normal precipitation.
 - Consistent with the general finding that coarse-scale models end to have limitations in capturing intense precipitation, but they produce too much drizzle under dry conditions.
 - Therefore, differences between the RCM and CFS skill are largest at the upper and lower ends of the reliability diagram for above- and below-normal precipitation, respectively.

Why do RCMs have limited skill?





- RCM do reproduce large-scale circulation pattern that closer to CFS
- However, CFS cannot reproduce itself.

Conclusions



- Dynamical downscaling by the multi-RCM produces finer-scale seasonal prediction based on the coarser resolution global forecast model. In terms of both climatology and anomaly from the long-term mean, the RCMs generate finer-scale features that are missing from CFS.
- Forecast skill of the downscaled P and T can vary for different metrics used in the cross validation.
- Using RMSE as the metrics, 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 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.

Thanks!



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- Many discussions with Kingtse Mo (CPC/NOAA), S.-Y. (Simon) Wang (USU), A. Wood (NOAA), T. Reichler (U. of Utah)
- Funded by NOAA CPPA program
- MRED participants to execute simulation and to share data

Yoon, J.-H., L. Ruby Leung, and J. Correia, Jr., 2012: Comparison of downscaled seasonal climate forecast during cold season for the U.S. using dynamic and statistical methods, *J. Geophys. Res*, doi:10.1029/2012JD17650

Thanks to MRED team



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Participants

- Jin Huang, NOAA Annarita Mariotti, NOAA John Roads (deceased), Scripps Raymond Arritt, ISU Chris Anderson, ISU
- Bill Gutowski, ISU
- H.-M. Henry Juang, NOAA
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- Chungu Lu, NOAA/GSD
- Lixin Lu, CIRA/CSU
- Ken Mitchell, NCEP
- Roger Pielke Sr., Univ. Colorado
- Siegfried Schubert, NASA/GSFC
- Gene Takle, ISU
- Patrick Tripp, Scripps/UCSD
- Yongkang Xue, UCLA
- Ronggian Yang, NOAA

Program manager

- Associate program manager
- Project originator, lead coordinator

Lead coordinator, MM5

- WRF-NMM-ESRL, MM5
- MM5
- CFS forcing, NOAA RSM
- Scripps RSM, central analysis
- WRF-ARW
 - CWRF
 - WRF-NMM-ESRL
 - RAMS
 - CFS forcing, operational transition
- RAMS
- NASA forcing
 - MM5, applications
 - Central analysis
 - Eta
 - CFS forcing

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WRF-NMM-ESRL, MM5

MM5

CFS forcing, NOAA RSM

Scripps RSM, central analysis

WRF-ARW

CWRF

WRF-NMM-ESRL

RAMS

CFS forcing, operational transition

RAMS

NASA forcing

MM5, applications

Central analysis

Eta

CFS forcing

Back-up slides



Anomaly correlation (Tas)



Multi-model ensemble WRF-ARW PNNL BCSD(CFS) 40N 30N **CWRF ISWS** CFS BCSD(RCM) 40N -6 30N ETA UCLA 120W 100W 80'W Bayesian(CFS) Mod 40N 30N Bayesian(RCM) Mod MM5 ISU 40N 30N RSM NCEP Bayesian(CFS) 40N 30N RSM ECPC Bayesian(RCM) 40N 30N 120W 100W RAMS CSU 40N 30N 120W 100W 80W

8⁰

°,

%. 69. 80W

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Anomaly correlation (Tas)





Spatial Correlation (Tas & Precipitation)





RMSE (Tas & Precipitation)



