Hybrid dynamical-statistical seasonal forecasts with weather types

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Underlying Concepts

- All subseasonal-to-seasonal (S2S) dynamical forecast systems have systematic errors.
- **Weather types (WTs)**, which are dominant large-scale atmospheric circulation patterns, may reflect the atmospheric spatial scales that are predictable on S2S timescales.
- **Hypothesis**: Seasonal forecasts are improved in a hybrid dynamical-statistical system in which model forecasts are merged with empirical relationships associated with pre-determined WTs.

Potential Benefits

- Pattern-dependent bias correction
- Empirical downscaling
- Correcting for underdispersive ensembles

The Approach

- December – February (DJF) precipitation forecasts over eastern U.S.
- 1981-2013 hindcasts of the NOAA GFDL Forecast oriented Low Ocean Resolution (FLOR) forecast model, initialized 1 November, 12 ensemble members

Three different forecast setups:

1) **P1**: Only ocean ICs, standard FLOR
2) **P1_FA**: Only ocean ICs, flux-adjusted FLOR to remove most SST biases
3) **P2_FA**: Both ocean and atmosphere initialized, flux-adjusted FLOR

- WTs calculated from FLOR and reanalysis daily 500 hPa geopotential height anomalies over North America
  - Five distinct WTs
- Three distinct forecast strategies
  1) **Raw model**: Forecast = ensemble mean precipitation
  2) **Unrectified**: Model 500 hPa height field mapped to *model* WT: Forecast = *model* WT composite precipitation
  3) **Rectified**: Model 500 hPa height field mapped to *observed* WT: Forecast = *observed* WT composite precipitation
- Evaluation metrics: Spearman correlation and root mean square error (RMSE)

General WT Features

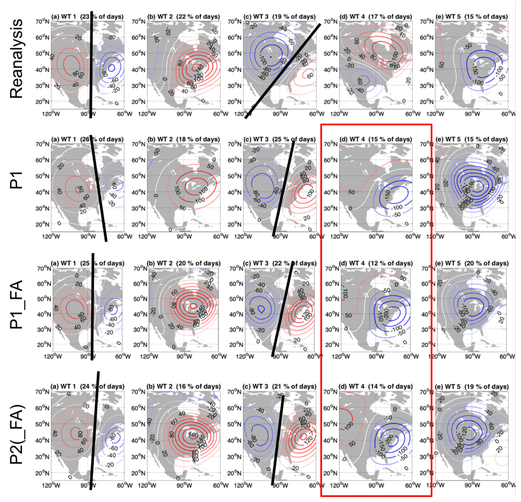

Figure 1. The 500 hPa geopotential height WTs in reanalysis data and in the three FLOR hindcast datasets. Composite 500 hPa geopotential height anomalies (gpm) for WTs 1-5 in (top row) NCEP/NCARv2 reanalysis data, (second row) P1 hindcasts, (third row) P1_FA hindcasts, and (bottom row) P2_FA hindcasts.

- All three FLOR hindcasts produce similar WTs, with strong circulation biases associated with WT4. Physical sources of bias are being investigated. (Fig. 1)
- WT-dependent precipitation biases clearly evident, particularly for WTs 2-5, with the sign of the bias varying with WT (Fig. 2)
- Climatological precipitation biases greatly reduced when reconstructing climatological precipitation with observed precipitation associated with model WTs (Fig. 3)

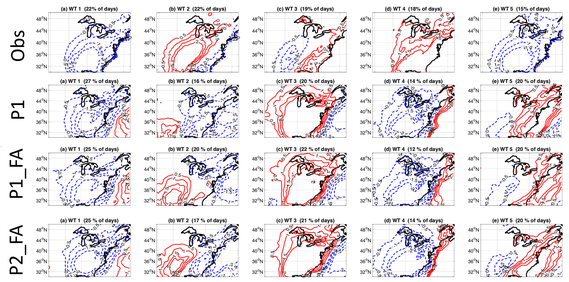

Figure 2. Composite precipitation anomalies associated with each WT. Composite precipitation anomalies (contour interval = 0.5 mm d^{-1}) for WTs 1-5 in observations (CPC Unified precipitation data), (second row) P1 hindcasts, (third row) P1_FA hindcasts, and (bottom row) P2_FA hindcasts.

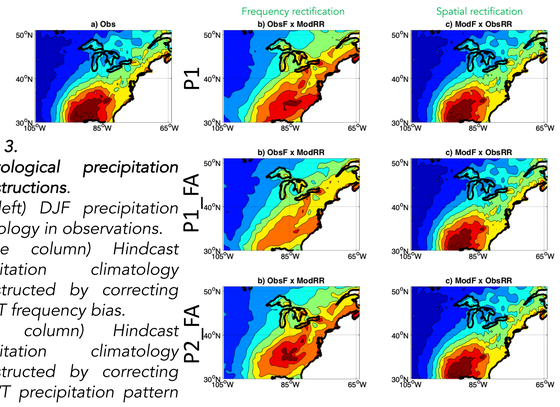

Figure 3. Climatological precipitation reconstructions. (Top left) DJF precipitation climatology in observations. (Middle column) Hindcast precipitation climatology reconstructed by correcting the WT frequency bias. (Right column) Hindcast precipitation climatology reconstructed by correcting the WT precipitation pattern bias.

DJF Precipitation Forecast Evaluations

RMSE

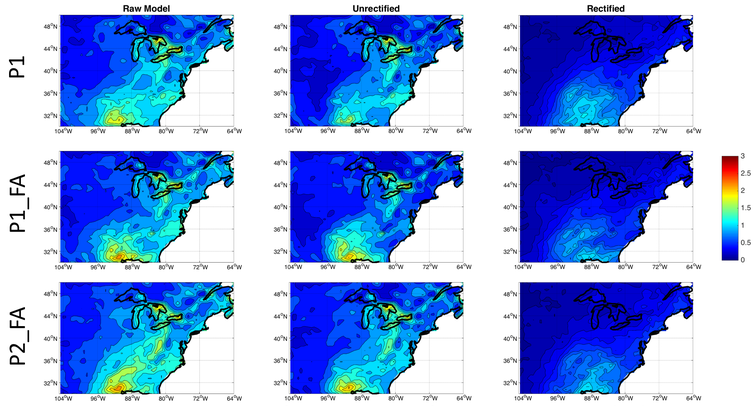

Figure 4. Root mean square error of DJF precipitation forecasts. RMSE (mm d^{-1}) of DJF 1981-2013 precipitation forecasts sorted by model setup (rows) and post-processing strategy (columns).

Correlation

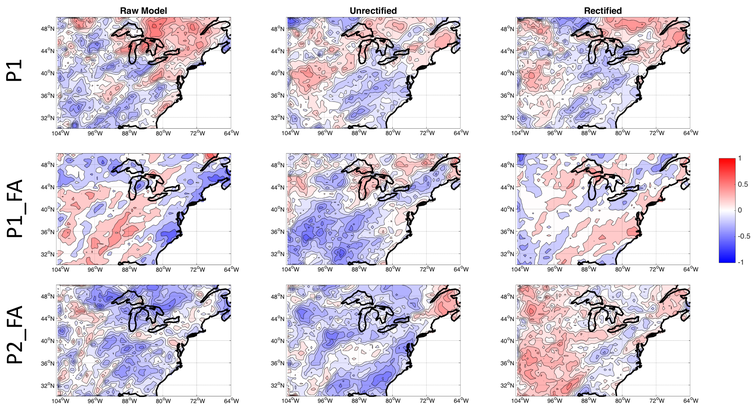

Figure 5. Pearson correlation skill of DJF precipitation forecasts. As in Fig. 4 but for the Spearman correlation coefficient between forecast and verification.

- RMSE similar for all raw FLOR forecasts (Fig. 4)
- Correlation skill poor over U.S. in raw FLOR forecasts (Fig. 5)
- Rectified WT hybrid dynamical-statistical forecast system greatly reduces RMSE relative to raw model forecasts for all three FLOR setups (Fig. 4)
- Correlation skill in rectified FLOR P2_FA forecasts greatly improved over central U.S. (Fig. 5)

Conclusions

- Weather Type-dependent biases evident in FLOR wintertime seasonal forecasts
- Flux-adjustment and inclusion of atmospheric ICs do not improve raw model DJF precipitation forecasts appreciably
- The rectified WT hybrid dynamical-statistical forecast system substantially reduces precipitation forecast RMSE and improves FLOR P2 correlation skill, especially over the central U.S.

Future work

- Investigate WT4 biases
- Comparison with standard bias correction
- Extension to probabilistic forecasts
- Application to sub-seasonal forecasts, using SubX/S2S Database

References

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