Model, data, experiment
The GEOS-5 AOGCM known as S2S-1.0 has been in service from June 2012 through January 2018 (Borovikov et al. 2017). The atmospheric component of S2S-1.0 is Fortuna-2.5, the same that was used for the Modern-Era Retrospective Analysis for Research and Applications (MERRA), but with adjusted parameterization of moist processes and turbulence. The ocean component is the Modular Ocean Model version 4 (MOM4). The sea ice component is the Community Ice CodE, version 4 (CICE). The land surface model is a catchment-based hydrological model coupled to the multi-layer snow model. The AGCM uses a Cartesian grid with a 1° x 1.25° horizontal resolution and 72 hybrid vertical levels with the upper most level at 0.01 hPa. OGCM nominal resolution of the tripolar grid is 1⁄4°, with a meridional equatorial refinement to 1⁄8°. In the coupled model initialization, selected atmospheric variables are constrained with MERRA. The Goddard Earth Observing System integrated Ocean Data Assimilation System (GEOS-iODAS) is used for both ocean state and sea ice initialization. SST, T and S profiles and sea ice concentration were assimilated.

For 35 years, every 5 days, a 9-month coupled seasonal hindcast has been initialized. In this study we included 4 mid-month hindcasts, concurrent with the hindcasts for the new forecast system S2S-2.1 (in production mode since December 2017).

Tropical Pacific Ocean SST S2S-1.0 forecasts in 1982-1998 and 1999-2016

Seasonal cycle bias for Equatorial Pacific Ocean SST indices

Forecast Skill
Anomaly Correlation Coefficient (ACC) is used as a measure of potential skill and Mean Square Skill Score (MSSS) as a measure of actual skill. MSSS is computed with respect to climatology.

\[
\text{MSSS} = \frac{\text{MSE}_\text{OFF} - \text{MSE}_\text{CLIM}}{\text{MSE}_\text{CLIM}}
\]

Here \( \text{MSE}_\text{OFF} \) is the temperature anomaly of the off hindcast and \( \text{MSE}_\text{CLIM} \) is 0.

Potential predictability P computed as the anomaly correlation for a case of one of the ensemble members treated as observations, averaged over all possible combinations of ensemble members.

\[
P = \frac{\langle AC(T_o, T_N) \rangle}{\langle AC(T_o, T_N) \rangle_{\text{potential predictability}}}
\]

\[
\text{ACC} = \frac{\langle AC(T_o, T_N) \rangle}{\langle AC(T_o, T_N) \rangle_{\text{climatology}}}
\]

References

Fig. 1. Reynolds SST used as ODAS observations for the initialization of the seasonal hindcasts/forecasts, and as SST validation. Shown here are the mean SST values over 1982-1998 and 1999-2016 periods for 4 seasons (Boreal winter, spring, summer and autumn), and the difference between these two fields.

Fig. 2. Spatial pattern of seasonal mean SST forecast departure from Reynolds SST for the 1982-1998 and 1999-2016 period, and anomaly correlation for a case of one of the ensemble members treated as observations, averaged over all possible combinations of ensemble members.

Fig. 3. Monthly mean SST forecast drift with respect to Reynolds. Solid lines show the 1982-1998 period, dashed lines correspond to the 1999-2016 period.

Fig. 4. The paper by Xue et al. (2013) was an inspiration for this study. Similar characteristics of ACC skill were for the CFSv2 and S2S-1.0 SST forecasts.

Fig. 5. Top row: SST ACC and MSSS for the Niño3.4 index. The Pearson correlation coefficient is shown in panels a) and b) with significance levels at 0.01 in panels c) and d), respectively. The anomaly correlation for a case of one of the ensemble members treated as observations, averaged over all possible combinations of ensemble members.

Fig. 6. Potential predictability P and the difference with the ACC, potential predictability computed as the anomaly correlation for a case of one of the ensemble members treated as observations, averaged over all possible combinations of ensemble members.

Fig. 7. ACC, MSSS, predictability skills for SST indices.