Advances in METplus Verification for Subseasonal to Seasonal Model Evaluation

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Introduction

The METplus system is a suite of verification and diagnostic tools in a consistent framework that are designed to facilitate quick setup. METplus contains several components, but at its core is the Model Evaluation Tools (MET) package for computing verification statistics. Additional components of METplus include METcalcpy, which contains python calculations of statistics and other indices and metrics, and METplotpy for creating graphics and displaying statistics. Recently, a set of process-oriented diagnostic and verification metrics have been added to the METplus system to examine the predictability of phenomena on subseasonal to seasonal time scales. The METplus GitHub repository (https://github.com/dtcenter/METplus) includes use cases, where users can change configuration settings to run the computations on different datasets. Here we will focus on four of these metrics, which fall into two categories, mid latitude weather and indices associated with the Madden Julian Oscillation (MJO).

Mid Latitude Metrics

There are two calculations added to METplus to evaluate different mid latitude weather events, atmospheric blocking and weather regimes. The weather regime classification begins by computing the optimal number of regimes using the sum of squared distances. From there, weather regime patterns and their frequency of occurrence are computed using K-means clustering. This clustering can be performed on the 500 hPa height data, or on reconstructed empirical orthogonal functions. Additionally, the frequency of occurrence of each classified weather regime can be computed over a user defined time period. Figure 1 shows the patterns of the first two weather regimes for the European Center for Medium Range Forecast Re-Analysis (ERA - top) and Global Forecast System (GFS - bottom). In total, there were six classified weather regimes. Output statistics can be performed on the classification and time frequency of regimes. Multi-category contingency table statistics computed on these classified weather regimes include a Heidke Skill Score (HSS) of 0.593, and a Hanssen-Kuipers Discriminant (HK) of 0.598.

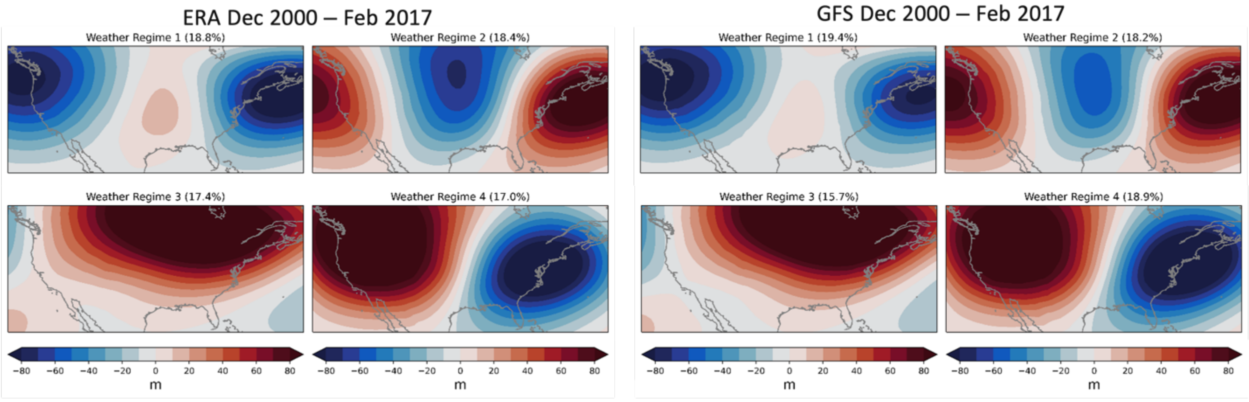

Figure 1. The first four weather regime patterns classified for the ERA (left) and GFS model (right). The frequency of each weather regime is given in parentheses.

The second mid latitude calculation, atmospheric blocking, uses approaches in both Pelly and Hoskins and Tibaldi and Molteni methods (Barnes et al, 2012). Specifically, atmospheric blocking events are identified by first locating reversals in the 500 hPa geopotential height gradient as blocked longitudes. This is followed by applying spatial and temporal thresholds to ensure the large-scale, quasi-stationary characteristics of blocking anticyclones are met. Some of the default characteristics are that a block must persist for at least 5 days and not travel more than 45 degrees downstream, although these options can be modified (Miller and Wang, 2019 and 2022).

MJO Indices

The two new MJO metrics that have been added to METplus include the Real-Time Multivariate MJO (RMM) Index and OLR-based MJO Index (OMI). Similar to the mid latitude calculations, these use ERA and GFS for the observations and model, however only graphics are output. The RMM is computed using latitudinal averages of outgoing longwave radiation (OLR), 850 hPa zonal winds, and 200 hPa zonal winds. The calculation follows Wheeler and Hendon 2004, and includes removal of the 120 day mean, regressing data onto the EOF patterns, and normalizing the principal components by the standard deviation. Figure 2 shows the phase diagram, RMM 1 and RMM 2 for 2022, and EOF1 for each variable from the RMM calculation.

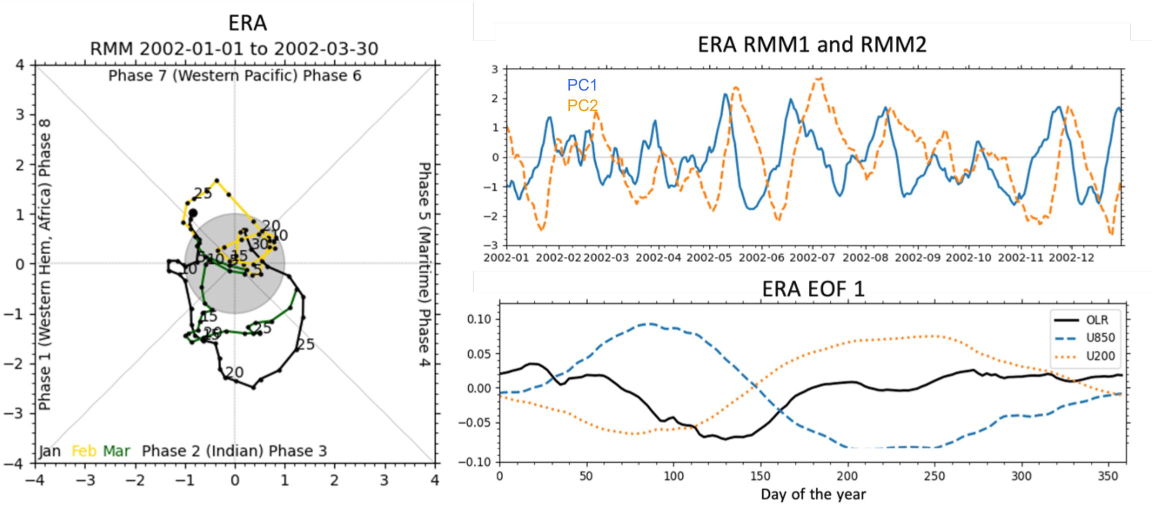

Figure 2. A phase diagram (left), RMM principal components 1 and 2 over 2022 (right, top), and the EOFs for all three variables (right, bottom).

The OMI computation is similar to RMM, but uses only outgoing longwave radiation. The first step is filtering to retain the frequencies associated with the MJO, which is set to be 29 – 90 days. Then, the OLR is projected on to the daily EOF patterns, and the principal components are normalized. Output from the OMI use case includes a phase diagram for both the model and observations which are like the one seen in Figure 2.

Summary

Many new process-oriented metrics have been added to the METplus system to examine the predictability of phenomena on subseasonal to seasonal time scales. These metrics include calculations of indices, output statistics, and graphics. The four metrics discussed here, along with all others, are designed to be flexible enough to use with different model and observation datasets, as well as user configurable options.

References

Barnes, E. A. ,J. Slingo, and T. Woollings, 2012: A methodology for the comparison of blocking climatologies across indices, models and climate scenarios. *Clim. Dyn.*, **38**: 2467–2481, 2012. doi: 10.1007/s00382-011-1243-6.

Miller, D. E., & Wang, Z., 2019: Skillful seasonal prediction of Eurasian winter blocking and extreme temperature frequency. Geophysical Research Letters, 46(20), 11530-11538.

Miller, D. E., & Wang, Z., 2022: Northern Hemisphere winter blocking: differing onset mechanisms across regions. Journal of the Atmospheric Sciences, 79(5), 1291-1309.

Wheeler, M. C., and H. H. Hendon, 2004: An all-season real-time multivariate MJO index: Development of an index for monitoring and prediction. *Mon. Wea. Rev.*, **132**, 1917–1932, doi:10.1175/1520-0493(2004)132<1917:AARMMI>2.0.CO;2.