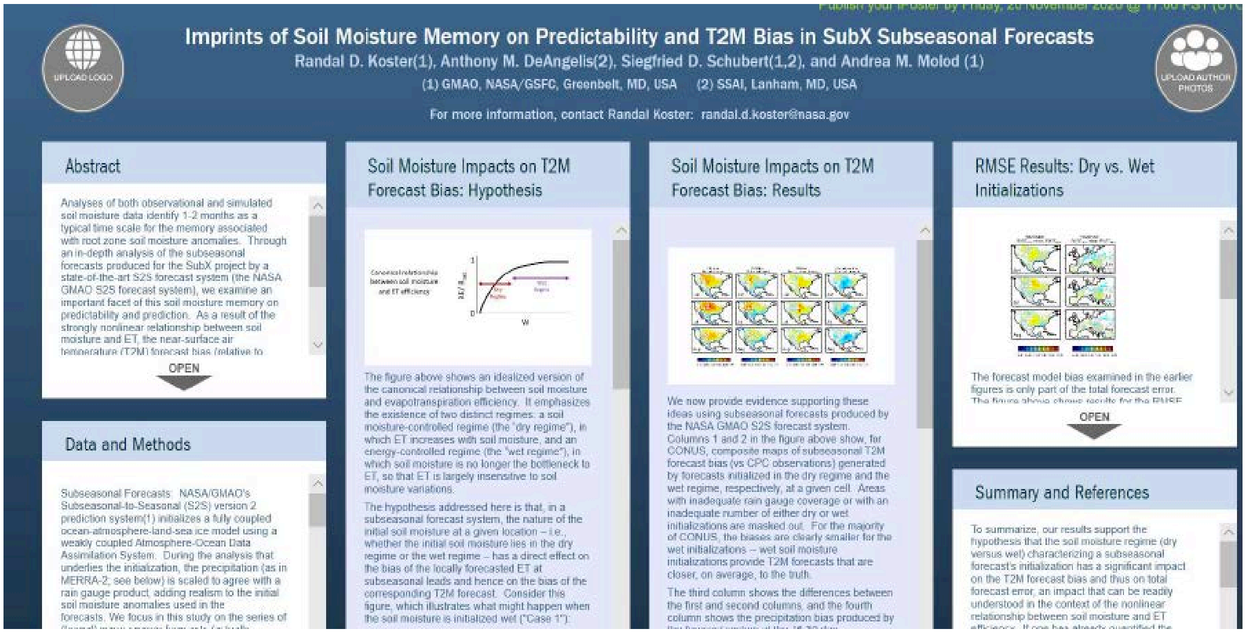
Imprints of Soil Moisture Memory on Predictability and T2M Bias in SubX Subseasonal Forecasts



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ABSTRACT

Analyses of both observational and simulated soil moisture data identify 1-2 months as a typical time scale for the memory associated with root zone soil moisture anomalies. Through an in-depth analysis of the subseasonal forecasts produced for the SubX project by a state-of-the-art S2S forecast system (the NASA GMAO S2S forecast system), we examine an important facet of this soil moisture memory on predictability and prediction. As a result of the strongly nonlinear relationship between soil moisture and ET, the near-surface air temperature (T2M) forecast bias (relative to independent observations) differs depending on the character of the local initial soil moisture -- a negative precipitation bias in the forecast system has a larger impact on T2M forecast bias when the initial soil moisture is dry as opposed to wet. Such results provide a pathway for improving the estimation of error in subseasonal T2M forecasts.

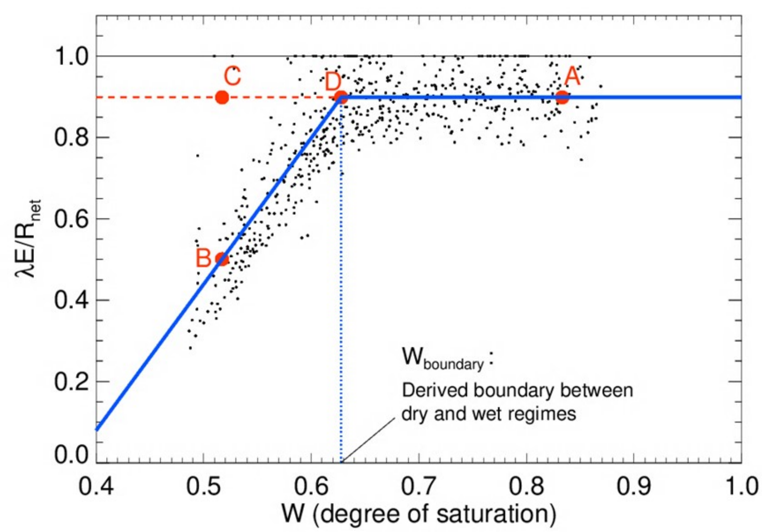
DATA AND METHODS

Subseasonal Forecasts: NASA/GMAO's Subseasonal-to-Seasonal (S2S) version 2 prediction system(1) initializes a fully coupled ocean-atmosphere-land-sea ice model using a weakly coupled Atmosphere-Ocean Data Assimilation System. During the analysis that underlies the initialization, the precipitation (as in MERRA-2; see below) is scaled to agree with a rain gauge product, adding realism to the initial soil moisture anomalies used in the forecasts. We focus in this study on the series of (boreal) warm season forecasts (actually, hindcasts) produced by this system. June, July, and August each provided 6 forecast start dates per year: forecasts were initialized five days apart, starting on June 5, July 5, and August 4. Given the 17-year period (1999-2015) considered, this translates to 102 independent forecasts per month, with each forecast consisting of 4 ensemble members. We focus here on averages over forecast days 16-30, i.e., forecasts at our chosen subseasonal lead.

MERRA-2: NASA/GMAO's MERRA-2 reanalysis(2) provides a comprehensive, consistent, state-of-the art picture of atmospheric and land surface fields over the period 1980-present. MERRA-2 root zone soil moisture, net radiation, and ET fields are used to characterize the nonlinear soil moisture-ET relationship critical to the T2M forecast bias analysis.

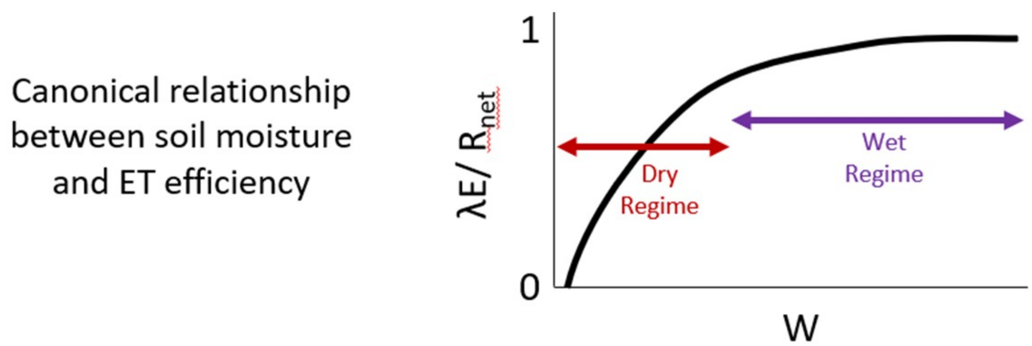
T2M Verification Data: We compare forecasted T2M at subseasonal leads to the independent, fully observations-based CPC temperature dataset(3).

Categorization of Dry and Wet Frecast Initializations: For the present analysis, it is critical to estimate from the model diagnostics the particular soil moisture $W_{boundary}$ that, for a given grid cell and time-of-year, divides the full soil moisture range into a dry regime (wherein ET increases with increasing soil moisture) and a wet regime (where it does not). Highlights of the approach we used as applied at a representative grid cell (in the central US) and representative month (June) are illustrated in this figure:



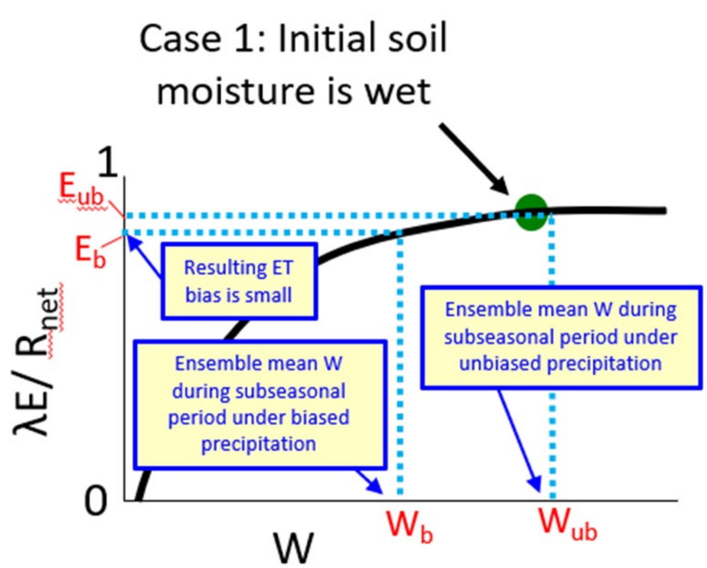
We first plot daily MERRA-2 values of W against corresponding values of λET/Rnet from all June days in 1980-1998. The wettest 10% of soil moistures in the plot are then identified, and the mean soil moisture and ET efficiency for that subset are used to position the point A in the figure. Similarly, averages over the driest 10% of soil moistures are used to position the point B. To determine $W_{boundary}$, a number of locations along the horizontal line AC are tested one by one; we identify the location (point D in the figure) such that, when the piecewise linear function (in dark blue) is fitted through A, D, and B, the function provides the closest approximation to the scatter of points in the plot. In essence, we determine the point D on the line AC such that the RMSE between the piecewise function and the individual λET/Rnet values is minimized.

SOIL MOISTURE IMPACTS ON T2M FORECAST BIAS: HYPOTHESIS



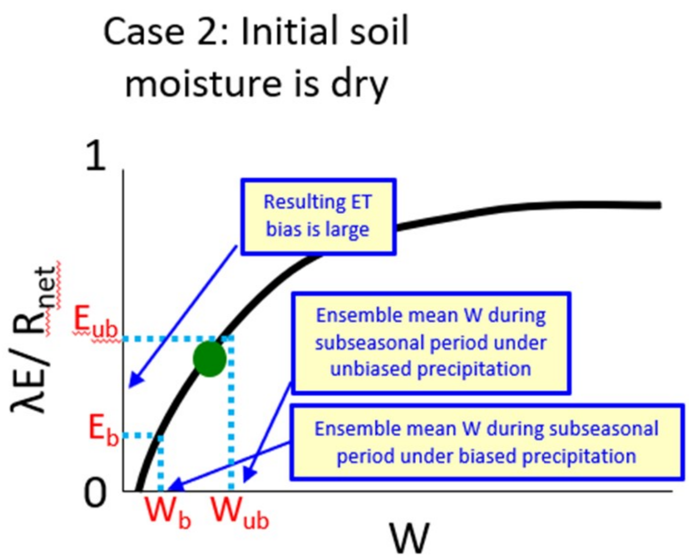
The figure above shows an idealized version of the canonical relationship between soil moisture and evapotranspiration efficiency. It emphasizes the existence of two distinct regimes: a soil moisture-controlled regime (the "dry regime"), in which ET increases with soil moisture, and an energy-controlled regime (the "wet regime"), in which soil moisture is no longer the bottleneck to ET, so that ET is largely insensitive to soil moisture variations.

The hypothesis addressed here is that, in a subseasonal forecast system, the nature of the initial soil moisture at a given location – i.e., whether the initial soil moisture lies in the dry regime or the wet regime – has a direct effect on the bias of the locally forecasted ET at subseasonal leads and hence on the bias of the corresponding T2M forecast. Consider this figure, which illustrates what might happen when the soil moisture is initialized wet ("Case 1"):



An unbiased (in terms of precipitation) forecast system might produce an ensemble of forecasted soil moistures with an average of Wub, associated with an average forecasted evapotranspiration efficiency of Eub. The actual forecast system, however, might have a negative precipitation bias that manifests itself at subseasonal leads, and the resulting forecasts of W and ET efficiency (Wb and Eb in the panel) would accordingly be lower. Note that the shape of the nonlinear relationship would lead to only a small difference between Eub and Eb, despite a large difference between Wub and Wb. That is, for a wet soil moisture initialization, the negative precipitation bias does not lead to a large bias in forecasted ET efficiency.

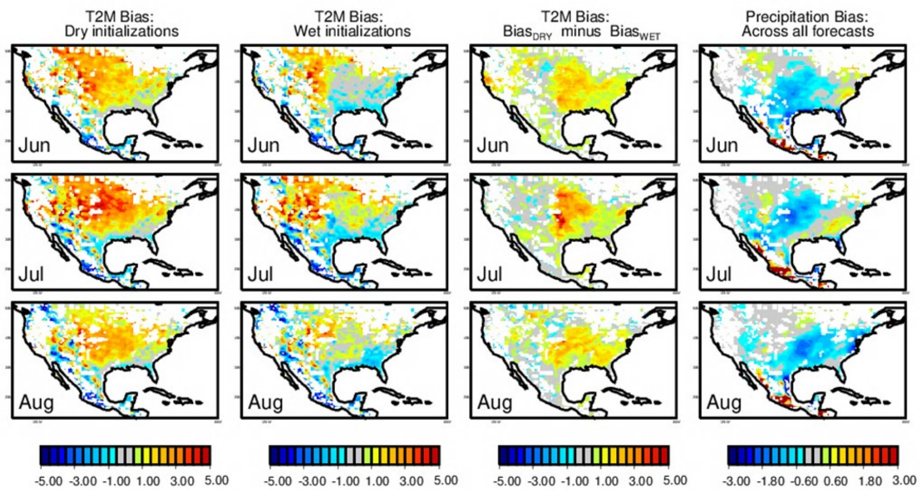
Consider now the contrasting impact of a dry soil moisture initialization ("Case 2"):



When initialized dry, the forecast system, faced with the same precipitation bias at subseasonal leads, would produce a large bias in the ET efficiency. The stark distinction in ET efficiency errors between Case 1 and Case 2 is, of course, a direct result of the nonlinearity of the soil moisture-ET efficiency relationship. To the extent that the net radiation itself shows relatively low variability when averaged over days 16-30 of a forecast (generally a good assumption), we see that wet and dry soil moisture initializations should have a distinctly different impact on the ET error itself.

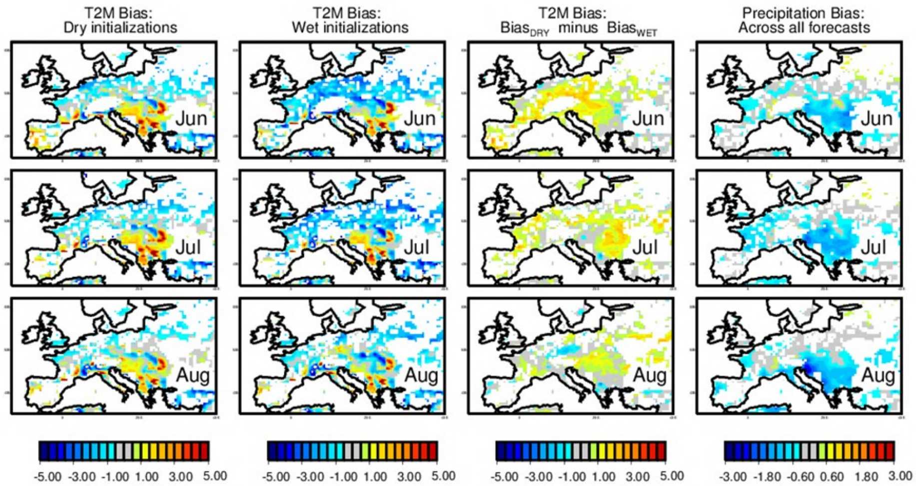
What should we accordingly expect regarding bias in forecasted air temperature? The connections between ET and T2M are well established. In the soil moisture-controlled ET regime, higher soil moistures lead to higher ET rates that in turn tend to induce lower T2M values through an increase in evaporative cooling. Because the negative precipitation bias induces a significant negative ET bias for Case 2, we should expect for Case 2 a concomitant positive increase in the T2M bias. For Case 1, on the other hand, the precipitation bias should have little effect on the T2M bias, at least through the ET pathway.

SOIL MOISTURE IMPACTS ON T2M FORECAST BIAS: RESULTS



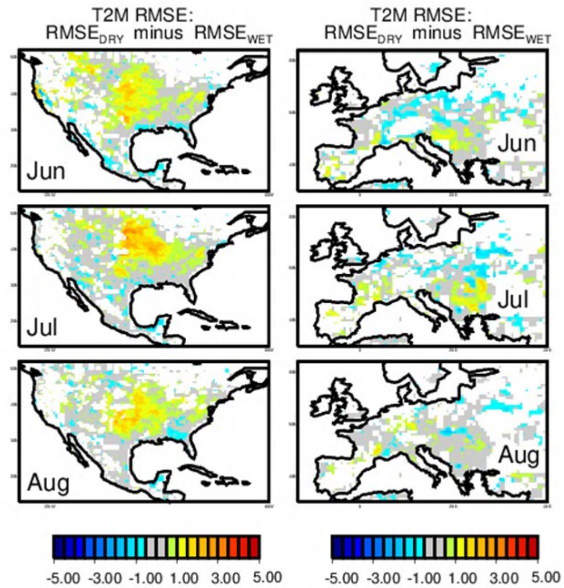
We now provide evidence supporting these ideas using subseasonal forecasts produced by the NASA GMAO S2S forecast system. Columns 1 and 2 in the figure above show, for CONUS, composite maps of subseasonal T2M forecast bias (vs CPC observations) generated by forecasts initialized in the dry regime and the wet regime, respectively, at a given cell. Areas with inadequate rain gauge coverage or with an inadequate number of either dry or wet initializations are masked out. For the majority of CONUS, the biases are clearly smaller for the wet initializations -- wet soil moisture initializations provide T2M forecasts that are closer, on average, to the truth.

The third column shows the differences between the first and second columns, and the fourth column shows the precipitation bias produced by the forecast system at the 16-30 day subseasonal lead. According to our hypothesis, the T2M bias difference should be positive where the forecasted precipitation is, on average, biased negative. This is indeed what is seen -- while the patterns in Columns 3 and 4 do not match exactly (as expected given sampling constraints and the fact that ET is not the only determinant of T2M across the continent), there is nonetheless a first-order agreement between the patterns. The T2M biases produced by the two forecast subsets, one initialized dry and the other initialized wet, differ by as much as 2-3K, particularly in July.



This next figure illustrates the same fields, but for Europe. The precipitation bias (column 4) is negative in many areas, and these areas are indeed where, at least for the most part, the difference in T2M forecast bias (dry initialization minus wet initialization) is positive (column 3) – the hypothesized behavior is present in Europe as well. However, other factors are also at play. In particular, modeled temperatures in the northern half of Europe are already biased low in this forecast system for reasons apparently unrelated to soil moisture. According to our hypothesis, the small but negative precipitation bias seen in the northern half of Europe encourages a bump upward in the T2M bias under dry initialization, but this inappropriate upward bump appears to mitigate the existing background cold bias through a compensation of errors. The forecast T2M bias in northern Europe is accordingly smaller in magnitude for dry initializations (compare columns 1 and 2).

RMSE RESULTS: DRY VS. WET INITIALIZATIONS



The forecast model bias examined in the earlier figures is only part of the total forecast error. The figure above shows results for the RMSE itself (which is often dominated by the bias in this forecast system). Specifically, it shows, for the two regions, the T2M forecast RMSE for dry initializations minus that for wet initializations.

Unlike bias, RMSE is a positive definite quantity, and thus the differences here are readily interpreted in terms of forecast skill – positive (negative) differences imply that the dry initialization subset produces larger (smaller) total forecast errors. For the central CONUS region, dry initializations clearly lead to higher total errors, and across CONUS, negative RMSE differences are small and infrequent. RMSE differences in Europe are smaller than those in CONUS, though in general, dry initializations lead to higher error in the southern half of Europe and wet initializations lead to higher error in the northern half. Again, a "compensation of errors" could explain the results in the northern half of Europe.

SUMMARY AND REFERENCES

To summarize, our results support the hypothesis that the soil moisture regime (dry versus wet) characterizing a subseasonal forecast's initialization has a significant impact on the T2M forecast bias and thus on total forecast error, an impact that can be readily understood in the context of the nonlinear relationship between soil moisture and ET efficiency. If one has already quantified the overall forecast biases (both temperature and precipitation) of a given modeling system through the analysis of historical forecasts, this mechanism should provide some guidance regarding the distinction between T2M forecast error under dry and wet initializations.

References:

(1) Molod, A. et al. GEOS-S2S version 2, The GMAO high-resolution coupled model and assimilation system for seasonal prediction. J. Geophys. Res. Atmos. 125, e2019JD031767 (2020). https://doi.org/10.1029/2019JD031767.

(2) Gelaro, R. et al. The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2). J. Climate 30, 5419–5454 (2017). doi:10.1175/JCLI-D-16-0758.1.

(3) https://www.esrl.noaa.gov/psd/data/ gridded/data.cpc.globaltemp.html

ABSTRACT

Analyses of both observational and simulated soil moisture data identify 1-2 months as a typical time scale for the memory associated with root zone soil moisture anomalies. Thus, if the land surface at some location in a subseasonal-to-seasonal (S2S) forecast system is initialized with a specific soil moisture anomaly, some aspect of that anomaly will still typically be present, say, 3-4 weeks into the forecast and can thereby influence evapotranspiration, surface runoff, and other hydrological processes at such leads. This contribution of soil moisture initialization to subseasonal hydrological predictability, however, varies significantly in space and time. Through in depth analysis of the subseasonal forecasts produced for the SubX project by a state-of-the-art S2S forecast system (the NASA GMAO S2S forecast system), and working from ideas provided by Seneviratne and Koster (2011), we demonstrate that the global distribution of the predictability of soil moisture is strongly tied to the ratio Var(W)/[Var(W)+Var(P)], where Var(W) is the variance (across years) of the total water in the soil column at the start of the forecast and Var(P) is the variance of the precipitation volume falling in the first 15 days of the forecast, i.e., prior to the subseasonal averaging period. This ratio is indeed found to explain most of the variance in soil moisture predictability across the globe in any given month as well as the seasonality in soil moisture predictability at most locations. The SubX data also indicate that evapotranspiration (ET) predictability (and, by extension, air temperature predictability) is strongly connected to this ratio as modified by independently established connections between soil moisture and ET. Finally, the initial soil moisture state for a forecast is shown to have a curious impact on predictability estimates: drier initial soils promote a higher predictability for soil moisture, whereas wetter initial soils promote a higher predictability for ET (and, again by extension, for air temperature).