Contribution of Land Surface States to Sub-seasonal Predictability

Randal Koster Global Modeling and Assimilation Office NASA/GSFC Greenbelt, MD USA

Theoretical Underpinning

An initialized land state can affect a forecast if the following two things happen:

a. The initialized anomaly is remembered into the forecast period. ("memory") Time 0 1 month 2 months

Which land states might have usable memory?



For which land states has an impact of initialization on forecasts been demonstrated?



For which land states has an impact of initialization on forecasts been demonstrated?



Soil moisture memory is well-established; estimated time-scales range from weeks to months.



"empirical autocorrelation function"

Vinnekov and Yeserkepova, J. Climate, 4, 66-79, 1991



~1-month-lagged autocorrelations of soil moisture (boreal summer)

Seneviratne et al., J. Hydromet., 7, 1090-1112, 2006



Conventional wisdom regarding control of soil moisture on evapotranspiration (and thereby on climate, forecasts)



Because of this relationship, the connection between soil moisture and the atmosphere (through the former's effect on evapotranspiration) is strongest in the <u>transition zones</u> between dry and wet areas.



Koster et al., Science, 305, 1138-1140, 2004

9

Explanation for why soil moisture feedback on the atmosphere is strongest in transition zones



Explanation for why soil moisture feedback on the atmosphere is strongest in transition zones



Explanation for why soil moisture feedback on the atmosphere is strongest in transition zones



So, for soil moisture, we seem to have both of these parts, at least in some areas.





Estimations of forecast skill associated with soil moisture initialization



Gist of experiment:

1. Perform two sets of forecast simulations:

(i) with accurate soil moisture initial conditions (ICs)

(ii) without accurate soil moisture ICs

- 2. Compare forecasted *P*, *T* to obs.
- 3. Compute soil moisture contribution to forecast skill:



Baseline: 100 Forecast Start Dates



Each ensemble consists of 10 simulations, each running for 2 months.

 \implies 1000 2-month simulations.

Skill measure: r² when regressed against observations



• We focus here on multi-model "consensus" view of skill.

• We focus here on JJA, the period when N.H. evaporation is strongest.

• We focus here on the U.S., for which:

- -- models show strong inherent predictability associated with land initialization (GLACE-1!)
- -- observations are reliable over the forecast period

Temperature forecasts: Increase in skill due to land initialization (JJA) (conditioned on strength of local initial soil moisture anomaly)



ones.

Precipitation forecasts: Increase in skill due to land initialization (JJA) (conditioned on strength of local initial soil moisture anomaly)



Local vs. Remote Soil Moisture Impacts on the Atmosphere

1. Consider local effects.



For example:

Wet soil \Rightarrow higher evap., lower sensible heat flux

This can affect <u>local</u> air temperature: ⇒ more evaporative cooling ⇒ lower air temperature

It can also affect local precipitation: ⇒ boundary layer modification ⇒ conditions more conducive (or perhaps less conducive) to onset of moist convection 2. Now consider potential remote effects:



Experimental Design

<u>Control</u>: Ensemble (768 members) of April-July simulations using atmosphere-land components of the GEOS-5 system, at $1^{\circ} \times 1^{\circ}$ resolution.

Experiment: Same as control, except:

(a) Smaller ensemble size (192 or 96 members)

(b) Precipitation in a selected region is not allowed to hit the surface during April-June, *forcing the surface to become dry there*.



The dry surface anomaly does (on average) induce a wave pattern in June-July...



The dry surface anomaly does (on average) induce a wave pattern in June-July...



... that does lead to remote, wavelike patterns in T2M and precipitation anomalies.



Induced 2-m Air Temperature Anomalies (K)



Important consideration: Given the large number of ensemble members needed to extract the signals of interest from the AGCM, we are talking here about shifts in PDFs. These shifts are subtle, and their relevance (e.g.) to forecasting large-scale dryness are yet to be demonstrated.





Jaison Thomas and Aaron Berg performed two sets of forecasts initialized on April 1 for each year in 1986-2005:

- 1) With realistic April 1 initializations of snow water equivalent, frozen soil moisture, and liquid soil moisture.
- 2) Without these realistic initializations.

Forecasted 15-day-average 2m temperatures were compared to observations (reanalysis).

As before,



Snow and soil water contributions to skill:



Ambadan et al., Climate Dynamics, 47, 49-65, 2016

Another study: Peings et al. (Clim. Dyn., 37, 985-1004, 2011) performed an analysis evaluating the contribution of snow initialization to temperature and pressure forecast skill.

Increase in anomaly correlation coefficient due to snow initialization: **2-m air temperature**



Snow initialization led to improvements in the 2-m temperature skill, mostly in the first 2 months following the March 1 initialization. The initialization had little impact on the large scale circulation, however, as indicated by predicted sea level pressure patterns.

(With thanks to Herve Douville, Meteo-France)

Lin et al. (GRL, 43, doi:10.1002/2016GL07 0966) examined the additional forecast skill achievable through the use of remote sensing in the initialization process.



Figure 2. The temperature prediction cumulative RMSE (cRMSE) difference between DA and OL. (a) Absolute value difference (K); (b) Percentage difference (%). Figures 2a (left) and 2b (left) (Figures 2a (right) and 2b (right)) show the difference between MOD (GRAMOD) and OL. The forecasts are initialized on 1 March. Negative values indicate reduced prediction errors and improved temperature predictions after using snow DA-constrained land initializations. The green boxes encompass two regions of interest for a further analysis in section 3.3. <u>Streamflow</u> forecasting via snow and/or soil moisture initialization is also a subseasonal-to-seasonal forecast topic.

Obvious: Larger snowpack ⇒ Increased streamflow during snowmelt season.

Less obvious: Impact of soil moisture...



Knowledge of winter snow, soil moisture ⇒ streamflow forecast skill

Performed experiments; estimated contribution to 3-month streamflow forecast skill from snow and soil moisture ICs:



 (\mathbf{r}^2) 0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0

Mahanama et al., J. Hydromet., 13,189-203, 2012



Vegetation state. An experiment similar to GLACE-2, but focusing on the impacts of initialized vegetation state on monthly forecast skill (using a land model with dynamic phenology) was recently performed. In fact, the effects of both soil moisture and vegetation initialization were quantified with the same framework and compared side-byside.



a. Soil Moisture Contribution to Forecast Skill: T-air

(Monthly forecasts)

EQ

30S



Koster and Walker, J. Hydromet., 16, 1456-1465, 2015



-0.20

-0.30

-0.08

-<u>0</u>. 10

Many indications of positive impact, but with magnitudes smaller than that for soil moisture



0.06 0.05 0.04 0.02 0.02 0.01 0.00 0.00 -0.01 -0.02 -0.02 -0.02 -0.02 -0.04

0.08

0.10

0.20

0.30



Observed differences between 9 coldest years and 9 warmest years (based on N.W. U.S. & S. E. Canada LST)

May Observed LST and SST

June Observed Precipitation

Observed/WRF-NMM simulated anomaly/difference of 2011 June Precipitation (mm day⁻¹)

SUBT: Subsurface temperature. The dotted areas denote statistical significance at the α =0.01 level of t-test values.

Xue et al., Env. Res. Lett., 11, 044018, 2016.

Some current challenges

- □ Quantifying the skill contributions further, with a large complement of models (soil moisture analyses relatively mature, but not other variables)
- □ More thorough theoretical analysis of memory and feedback mechanisms; characterizing "nature's" land-atmosphere coupling strength.
- □ Inclusion of additional variables into operational forecast systems (e.g., phenology)
- □ Taking advantage of the potential for conditional forecasts
- Need for better data for initialization: optimizing use of limited measurement resources to maximize impact on forecast skill, and tapping into as-yet-unused data sources

Thank you. Questions?

Extra Slides

Note the contradiction between diagnosed coupling strength locations (from earlier) and locations where skill appears:

Reasons for the discrepancy are somewhat unclear but may be related to:

- -- different set of models, with different biases (different transition zones)-- spatial differences in memory
- -- ability to produce a feedback loop
- ("coupled mode") in the forecast system

Skill levels (extreme deciles)

Note the contradiction between diagnosed coupling strength locations (from earlier) and locations where skill appears:

Reasons for the discrepancy are somewhat unclear but may be related to:

- -- different set of models, with different biases (different transition zones)
- -- spatial differences in memory

-- ability to produce a feedback loop ("coupled mode") in the forecast system

Skill levels (extreme deciles)

perhaps not the primary reason, but scientifically exciting – worth a quick look!

Global averages of contributions over areas with adequate rain gauge density

1-month air temperature forecasts

Induced 2-m Air Temperature Anomalies (K)

This, along with a suite of additional "dry surface" experiments, suggests a feedback loop:

