Role of soil moisture for (sub-)seasonal prediction

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Abstract

Soil moisture is an important contributor to (sub-) seasonal predictability because of 1) its distinctive memory characteristics and 2) its feedback to atmospheric variables (temperature, precipitation). In particular, an observational analysis suggests that soil moisture anomalies strongly affect temperature extremes over a large fraction of the globe. Multi-model analyses from the 2nd phase of the Global Land-Atmosphere Coupling Experiment (GLACE-2) identify hot spots of coupling but appear to underestimate the effect of moisture deficits on temperature compared to observations-based metrics. Further investigations will be required to better understand these discrepancies. Finally, soil moisture memory is also relevant for (sub-) seasonal hydrological forecasts of soil moisture and streamflow, both in relation with soil moisture initialization and in the temporal propagation of skill from forecasted atmospheric variables to the land hydrological variables.

1 Introduction

Soil moisture displays distinctive persistence characteristics, with memory effects reaching up to several weeks to months, and some cases years (e.g. Vinnikov et al. 1996, Koster and Suarez 2001, Schubert et al. 2004, Seneviratne et al. 2012, Orth and Seneviratne 2012). Furthermore, soil moisture-climate interactions play a central role within the climate system, through the impacts of soil moisture on plant evapotranspiration and photosynthesis (Seneviratne et al. 2010; Fig. 1a). As much as 60% of all water precipitated on land is returned to the atmosphere through land evapotranspiration (Oki and Kanae 2006), and the energy required for this process uses more than half of all available net radiation (e.g. Trenberth et al. 2009). Hence impacts of soil moisture on evapotranspiration affect both land moisture and heat inputs to the atmosphere. Recent research has in particular highlighted the strong impacts that soil moisture-atmosphere interactions have on temperature extremes and drought development in several regions (e.g. Seneviratne et al. 2006a, Hirschi et al. 2011, Mueller and Seneviratne 2012; Fig. 1b). This extended abstract provides a brief overview on the potential relevance of soil moisture in the context of seasonal forecasting.

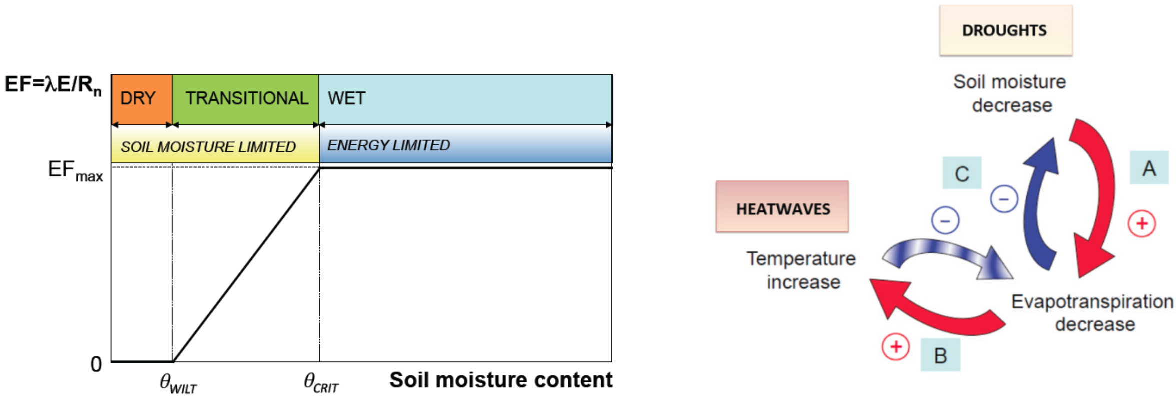

Figure 1(a, left) Conceptual schematic illustrating the dependence of evaporative fraction EF (i.e. latent heat flux divided by net radiation) on soil moisture. θ_{CRIT} denotes the critical soil moisture level, and θ_{WILT} the plant wilting point. Surface fluxes are strongly dependent on soil moisture between these two bounds (transitional climate); (b, right) Processes contributing to soil moisture-temperature coupling and feedback loop. Positive arrows (red) indicate processes that lead to a drying/warming in response to a negative soil moisture anomaly and blue arrows denote potential negative feedbacks (the hatched blue arrow indicates the tendency for enhanced temperature to lead to more evaporative demand; if this results in an evapotranspiration increase, this in turn leads to a further drying of the soil and thus to a positive feedback loop). [Adapted from Seneviratne et al. 2010, Earth-Science Reviews]

2 Soil moisture memory

Being a storage component of the climate system, the soil can "remember" past atmospheric anomalies (precipitation, temperature, radiation), as these result in soil moisture anomalies with a given decay time scale. Typically, soil moisture anomalies extend up to a few weeks and months (e.g. Vinnikov et al. 1996, Seneviratne et al. 2006b, Orth and Seneviratne 2012), and may in some case display year-to-year carry-over effects (e.g. Schubert et al. 2004, Seneviratne et al. 2012a). This soil moisture-induced memory is important for seasonal forecasting in several regions, in particular in mid-latitude regions, where soil moisture is a strong control for surface climate, and oceanic forcing only plays a minor role in relative terms (e.g. Koster et al. 2000, 2010b).

Two main controls of soil moisture memory within a given time frame are 1) initial soil moisture anomalies and 2) the atmospheric forcing variability over the time frame (Delworth and Manabe 1988; Koster and Suarez 2001; Seneviratne and Koster 2012; Fig. 2). In addition, soil moisture memory is reduced by the sensitivity of evapotranspiration and runoff to soil moisture content, and enhanced (reduced) by positive (negative) feedbacks with the atmosphere (Koster and Suarez 2001, Seneviratne and Koster 2012).

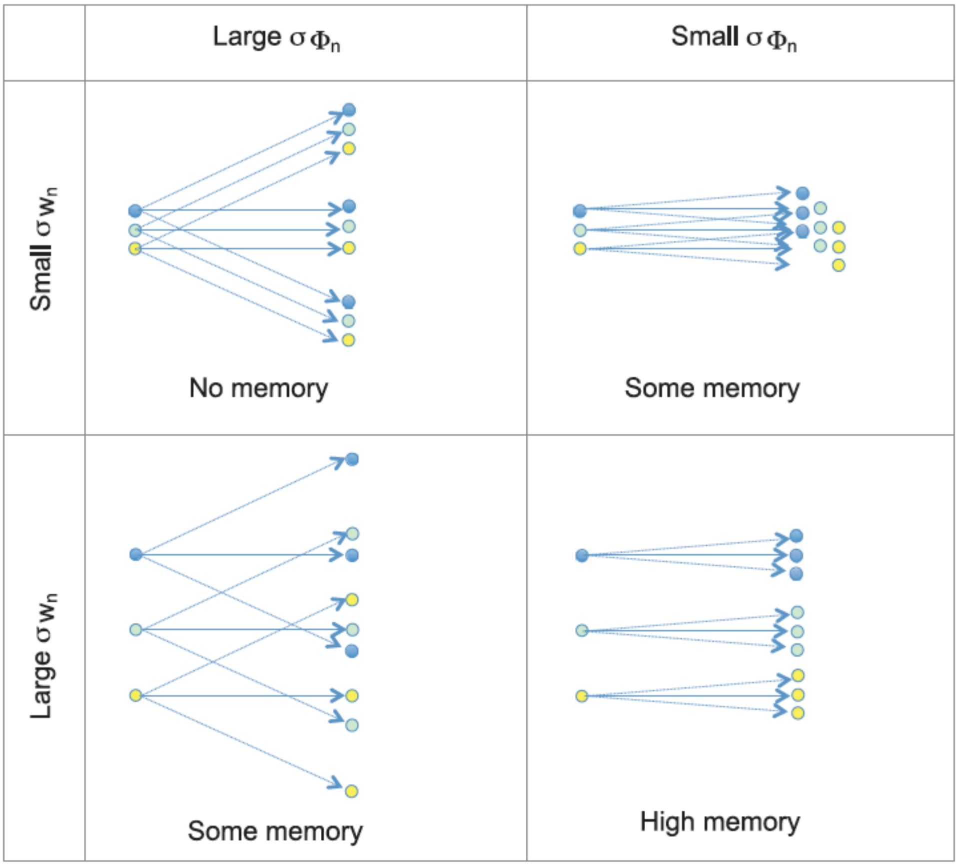

Figure 2. Illustration of the combined role of initial soil moisture variability (σ_{wn}) and subsequent atmospheric forcing variability ($\sigma_{\Phi n}$) in enhancing / reducing soil moisture memory. [From Seneviratne and Koster 2012].

3 Impact of surface moisture deficits for (sub-) seasonal forecasting: Multi-model results (GLACE-2 experiment)

As part of the 2nd phase of the Global Land-Atmosphere Coupling Experiment (GLACE; Koster et al. 2010a, 2011), the forecasting skill associated with realistic soil moisture initialization has been recently estimated with a multi-model experiment for the boreal spring-summer season (April-August). The results reveal skill increase in some regions, in particular for temperature and for extreme soil moisture initializations (Koster et al. 2010a, 2011). For precipitation, skill is generally weak (Koster et al. 2010b, 2011). When evaluating the actual model's skill with observations, it is found to be much smaller than the potential predictability derived from the models alone (see Fig. 3). Evidence suggests that the highest simulated skill is found in regions with strong soil moisture-atmosphere coupling and high-quality precipitation observations (Koster et al. 2011), the latter being critical for the quality of the soil moisture initialization in forecasts.

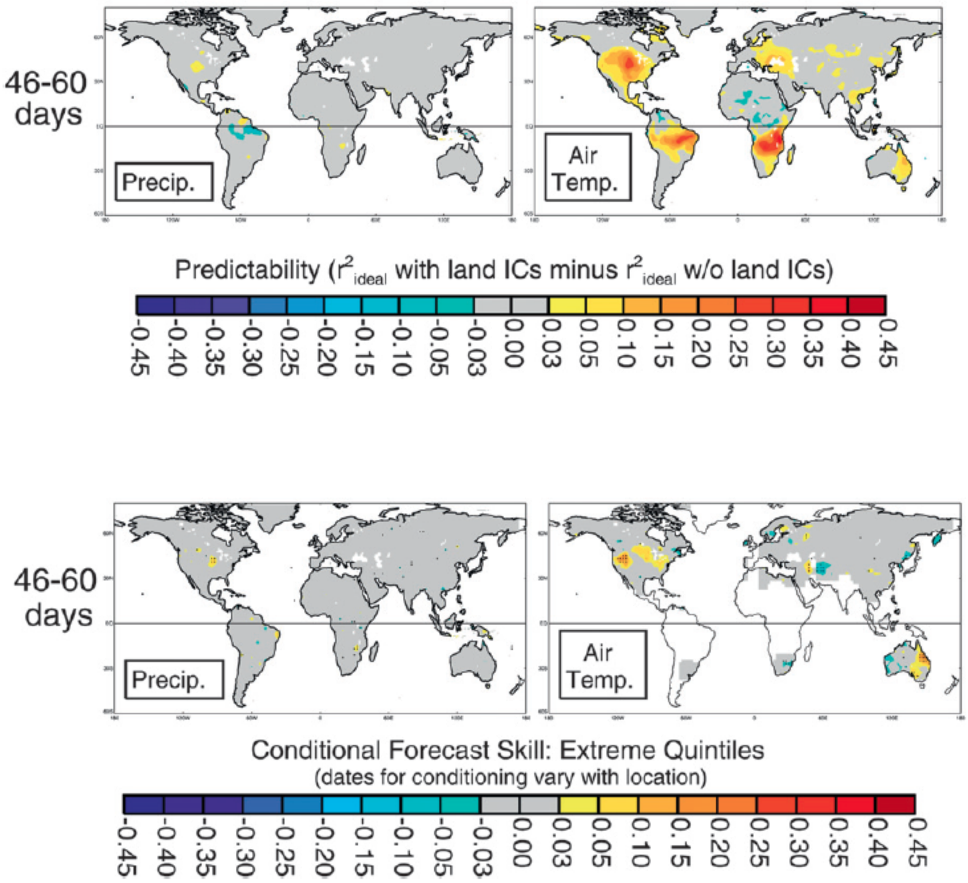

Figure 3. GLACE-2 results. (top row) Multimodel-consensus estimate (i.e. potential predictability) of (left) precipitation and (right) air temperature predictability associated with soil moisture initial conditions (IC) for 46-60-day forecast period —in essence a quantification of how one ensemble member in a given forecast reproduces the synthetic truth produced by the remaining ensemble members in that forecast; (bottom row) (left) Precipitation and (right) air temperature forecast skill (r^2 against observations for model ensemble with realistic initialization vs model ensemble with random initialization) for 46-60-day forecast period for a 40% subset of the 15-day forecast periods during JJA: those periods for which the local initial soil moisture content is in the top fifth or the bottom fifth of all realized values. Dots are shown where the plotted results are statistically different from zero at the 99% confidence level; white areas lack available validation data. [From Koster et al. 2011].

4 Impact of surface moisture deficits for forecasting of temperature extremes: Evidence from observations

While most of the evidence on soil moisture-atmosphere coupling has been traditionally derived with models (e.g. Koster et al. 2004, Seneviratne et al. 2006a, Koster et al. 2010; see also section 3.), it is important to identify observational diagnostics for this coupling that can be used to validate its representation in models.

In a recent study (Mueller and Seneviratne 2012, hereafter MS12), soil moisture-temperature coupling is investigated using observational data (gridded observations, reanalysis data). Thereby, normalized surface precipitation deficits (computed using the Standardized Precipitation Index – SPI) are used as proxy for soil moisture and related to indices of hot extremes. The study focuses on the relationship between the number of hot days (NHD) in the respective regions' hottest month and preceding precipitation deficits. The focus on each region's hottest month allows the derivation of a globally valid estimate of coupling, which is for instance also relevant for Southern Hemisphere regions (unlike model experiments of the 1st and 2nd phases of the GLACE experiment, which focus on boreal (spring to) summer only). The MS12 study identifies that wide areas of the world display a strong relationship between the number of hot days in the regions' hottest month and preceding precipitation deficits. (Figure 4)

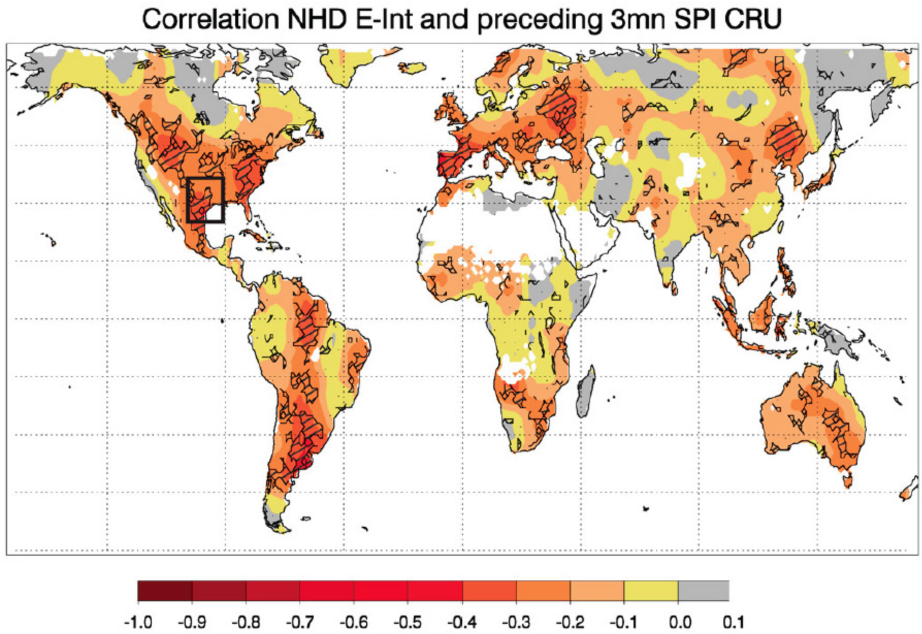

Figure 4. Relation between number of hot days (NHD) in hottest month of each year and preceding precipitation deficits (SPI) from correlations of NHD in hottest month with 3-month SPI in preceding month. All maps have been smoothed with a boxcar filter of width 10. Significant levels (90%) are not smoothed (hatched). White areas indicate missing values. The employed datasets are ERA-Interim (E-Int) for NHD and CRU for SPI. In 2011 both SPI and NHD displayed record high values in Texas (box). [From Mueller and Seneviratne 2012]

Consistent with this result, MS12 identify that the occurrence probability of an above-average number of hot days is over 70% after precipitation deficits in most parts of South America as well as the Iberian Peninsula and Eastern Australia, and over 60% in most of North America and Eastern Europe, while it is below 30–40% after wet conditions in these regions (Figure 5).

Furthermore, quantile regression analyses reveal that the impact of precipitation deficits on the number of hot days is asymmetric (Figure 6), i.e. extreme high numbers of hot days are most strongly influenced. These results are consistent with those of a previous study focusing on Southeastern Europe (Hirschi et al. 2011), and another recent investigation considering the whole European continent (Quesada et al. 2012). This relationship also applies to the 2011 extreme event in Texas (MS12; see box on Fig. 4).

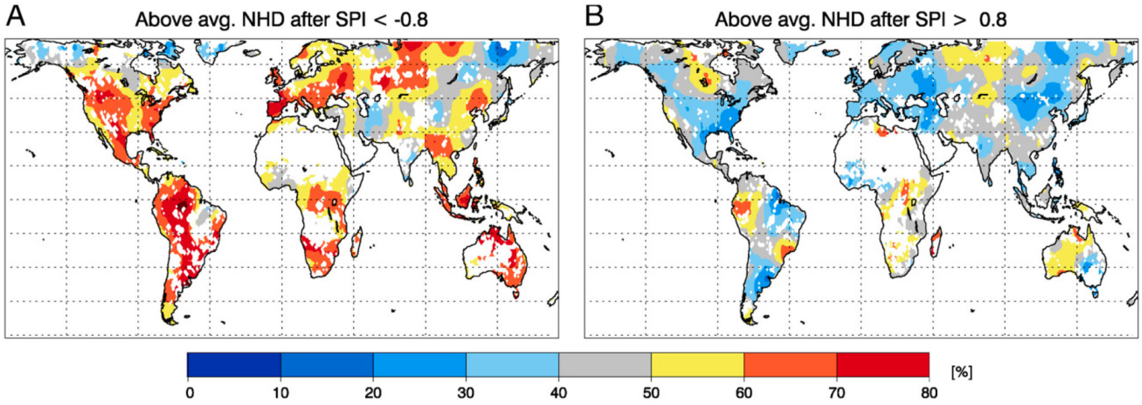

Figure 5. Hot day occurrence probability after dry versus wet conditions. Occurrence probability for above-average number of hot days in the respective hottest month of each year following low 3-month SPI values (dry conditions, A) and high 3-month SPI values (wet conditions, B). Values are given in percentage of years with above-average NHD from total number of low and high SPI years, respectively. Values that are based on a composite of less than 4 years are not shown (white areas). The employed datasets are ERA-Interim for NHD and CRU for SPI. [From Mueller and Seneviratne 2012]

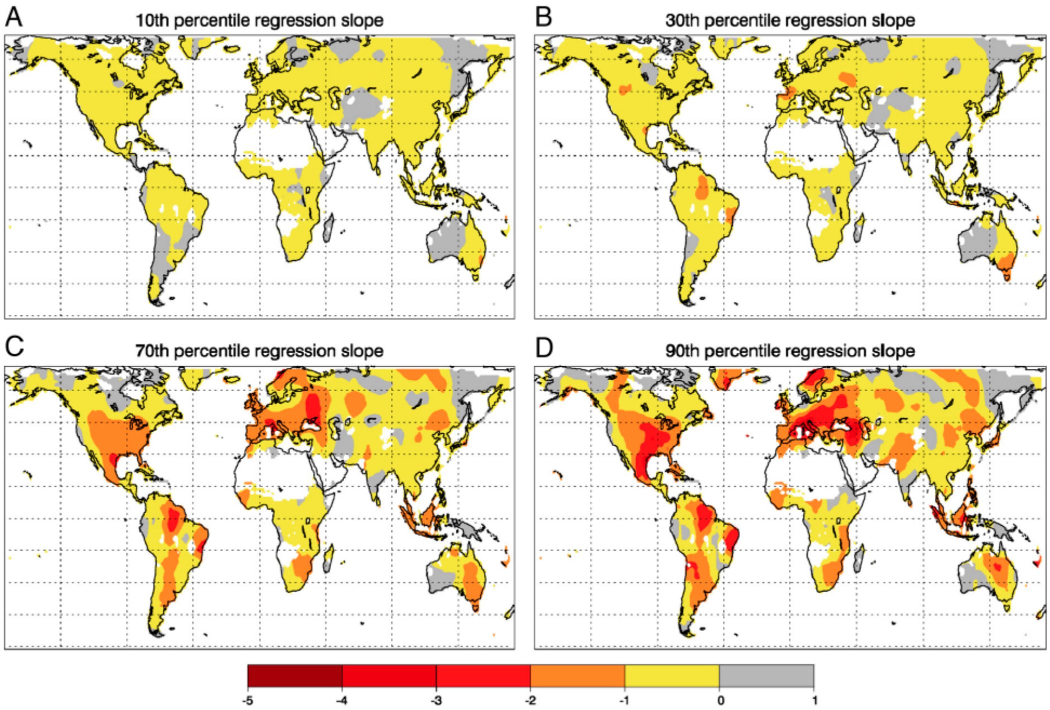

Figure 6. Quantile regression of number of hot days in hottest month of each year and preceding 3-month SPI. Slope of regression lines of 10th (A), 30th (B), 70th (C) and 90th (D) percentiles. White areas indicate missing values. The employed datasets are ERA-Interim for NHD and CRU for SPI. [from Mueller and Seneviratne 2012]

Interestingly, the MS12 analysis indicates a possibly underestimated forecasting skill from soil moisture initialization in the GLACE-2 multi-model experiment (Koster et al. 2010a, 2011; Section 3). Potential explanations include the following: 1) focus on regional hottest month in MS12 rather than April-August period in GLACE-2; 2) poor performance of (some of) the participating GLACE-2 models; 3) other issues with GLACE-2 set-up (e.g. soil moisture initialization); 4) focus on extreme temperatures vs mean temperatures; 5) inclusion of non-causal relationships in SPI-NHD correlations. Further investigations will be required to better identify the underlying causes for these discrepancies. It is noteworthy that the potential skill of the GLACE-2 models (Fig. 3, top) shares many commonalities to the SPI-NHD relationships (e.g. correlations in Fig. 4), despite the differences in considered time frames (see point 1) above). This may point to issues with the quality of soil moisture initialization in the GLACE-2 experiment, although potential predictability is necessary lower than actual predictability.

5 Relevance of soil moisture initialization for hydrological forecasts

While land hydrology plays an important role for (sub-) seasonal forecasts of atmospheric variables in several regions (see Sections 4. and 5.), soil moisture persistence characteristics are necessarily also crucial for hydrological (sub-) seasonal forecasts, for variables such as soil moisture and streamflow (e.g. Koster et al. 2010a, Mahanama et al. 2012). This is important for water resources planning and management.

In a new analysis, Orth and Seneviratne (2013, submitted) have quantified the contribution of several factors to the forecast skill of soil moisture and streamflow in catchments in Switzerland (Fig. 7). The investigations use a simple water-balance model calibrated with runoff observations (Orth et al. 2013). The results reveal an essential role of soil moisture initialization, but also substantial improvements yielded with the use of ECMWF precipitation forecasts. It is noteworthy that the latter have a positive impact over a time frame that is longer than that over which the ECWMF precipitation forecasts show skill, because of the propagation of forecasted precipitation anomalies to long-lasting soil moisture anomalies (Orth and Seneviratne 2013, submitted). Although snow initialization does not contribute strongly to skill for the average of the considered catchments (Fig. 7), it does have an important impact in several high-altitude catchments. In these catchments, also the role of temperature and radiation is enhanced, due to their impact on snowmelt (Orth and Seneviratne 2013, submitted).

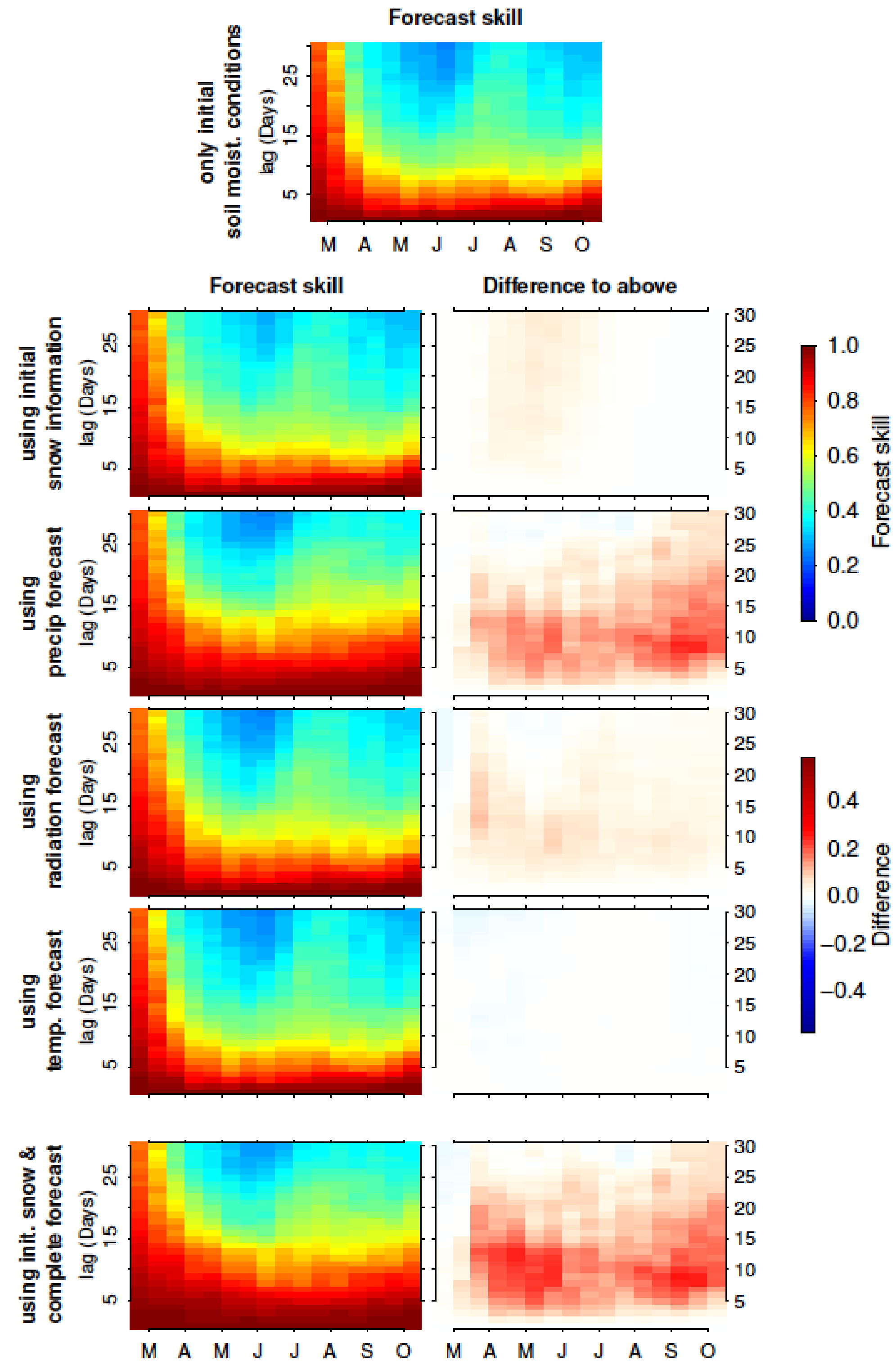

Figure 7. Soil moisture forecast skill for catchments in Switzerland using a simple water-balance model calibrated with streamflow observations; "true" soil moisture or snow refers to the model's own soil moisture and snow: Forecast skill from "true" initial soil moisture and climatological forcing (upper row), and improvements resulting from "true" initial snow information (second row), the use of ECMWF precipitation (third row), radiation (fourth row), or temperature forecasts (fifth row), and the use of all these information sources together (bottom row). Skills shown for lead times between 1 and 32 days and for months between March and October as a mean of all catchments. [from Orth and Seneviratne 2013, submitted]

6 Summary and conclusions

This extended abstract provides an overview on recent findings with respect to the role of soil moisture for (sub-) seasonal predictions. In particular the impact of soil moisture on temperature (extremes) has been highlighted in a number of publications. The recent analysis of Mueller and Seneviratne (2012) points to a large number of regions with strong relationships between the number of hot days in the regions' hottest month and preceding precipitation deficits. The identified hot spots appear more extended than in previous modeling experiments investigating the impacts of soil moisture on atmospheric variability. Additional analyses will be necessary to clarify these discrepancies. Overall, the role of soil moisture memory is found to be essential for (sub-) seasonal forecasting of both atmospheric and hydrological variables in several regions across the globe. For atmospheric variables, also the coupling between soil moisture anomalies and atmospheric variables (temperature, precipitation) is an important component. Further combined observations- and model-based analyses will help reduce uncertainties and increase forecasting skill from soil moisture initialization in coming years.

7 References

Delworth, T.L., and S. Manabe (1988), The influence of potential evaporation on the variabilities of simulated soil wetness and climate. J. Climate, 1, 523–547.

Hirschi, M., S.I. Seneviratne, V. Alexandrov, F. Boberg, C. Boroneant, O.B. Christensen, H. Formayer, B. Orlowsky, and P. Stepanek (2011), Observational evidence for soil moisture impact on hot extremes in southeastern Europe. Nature Geoscience, 4, 17–21.

Koster, R.D., M.J. Suarez, and M. Heiser (2000), Variance and predictability of precipitation at seasonal-to-interannual timescales. J. Hydrometeorol. 1 (1), 26–46.

Koster, R.D., and M.J. Suarez (2001), Soil moisture memory in climate models. J. Hydrometeorol., 2, 558–570.

Koster, R.D., et al. (2004), Regions of strong coupling between soil moisture and precipitation. Science, 305, 1138–1140.

Koster, R.D., S.P.P. Mahanama, B. Livneh, D.P. Lettenmaier, and R.H. Reichle (2010a), Skill in streamflow forecasts derived from large-scale estimates of soil moisture and snow. Nature Geoscience, 3, 613–616.

Koster, R.D., et al. (2010b), Contribution of land surface initialization to subseasonal forecast skill: First results from a multi-model experiment. Geophys. Res. Lett., 37, L02402.

Koster, R.D., et al. (2011), The Second Phase of the Global Land-Atmosphere Coupling Experiment: Soil Moisture Contributions to Subseasonal Forecast Skill. J. Hydrometeorol., 12, 805–822.

Mahanama, S., B. Livneh, R. Koster, D. Lettenmaier, and R. Reichle (2012), Soil moisture, snow, and seasonal streamflow forecasts in the United States. J. Hydrometeorology, 13(1), 189-203, doi: 10.1175/JHM-D-11-046.1.

Mueller, B., and S.I. Seneviratne (2012), Hot days induced by precipitation deficits at the global scale. Proc. Natl. Acad. Sci., 109 (31), 12,398–12,403.

Oki, T., and S. Kanae (2006), Global hydrological cycles and world water resources. Science 313, 1068–1072.

Orth, R., and S. I. Seneviratne (2012), Analysis of soil moisture memory from observations in Europe. J. Geophys. Res., 117, D15,115, doi:10.1029/2011JD017366.

Orth, R., R.D. Koster, and S.I. Seneviratne (2013), Inferring soil moisture memory from runoff observations. *J. Hydrometeorology*, in press.

Orth, R., and S. I. Seneviratne (2013), Predictability of soil moisture and runoff on subseasonal timescales: A case study for Switzerland. Submitted to J. Geophys. Res.

Quesada, B., R. Vautard, P. Yiou, M. Hirschi, and S.I. Seneviratne (2012), Asymmetric European summer heat predictability from wet and dry southern winters and springs. Nature Climate Change, 2, 736–714.

Schubert, S.D., M.J. Suarez, P.J. Pegion, R.D. Koster, and J.T. Bacmeister (2004), On the cause of the 1930s Dust Bowl. Science 303, 1855–1859.

Seneviratne, S.I., D. Lüthi, M. Litschi, and C. Schär (2006a), Land-atmosphere coupling and climate change in Europe. Nature, 443, 205–208.

Seneviratne, S. I., et al. (2006b), Soil moisture memory in AGCM simulations: Analysis of Global Land-Atmosphere Coupling Experiment (GLACE) data. J. Hydrometeorol., 7, 1090–1112.

Seneviratne, S. I., T. Corti, E.L. Davin, M. Hirschi, E.B. Jaeger, I. Lehner, B. Orlowsky, and A.J. Teuling (2010), Investigating soil moisture-climate interactions in a changing climate: A review. Earth-Science Reviews, 99, 125–161.

Seneviratne, S.I., and R.D. Koster (2012), A revised framework for analyzing soil moisture memory in climate data: Derivation and interpretation. J. Hydrometeorol., 13, 404–412.

Seneviratne, S.I., et al. (2012), The Rietholzbach research site: Analysis of 32-year hydroclimatological time series and 2003 drought at a Swiss pre-alpine catchment. Water Resources Research, 48, W06,526.

Trenberth, K.E., J. Fasullo, and J. Kiehl (2009), Earth's global energy budget. B. Am. Meteorol. Soc. 90 (3), 311–323.

Vinnikov, K.Y., A. Robock, N.A. Speranskaya, and C.A. Schlosser (1996), Scales of temporal and spatial variability of midlatitude soil moisture. Journal of Geophysical Research, 101, 763–7174.