Use of a standardized runoff index for characterizing hydrologic drought

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[1] Many current metrics of drought are derived solely from analyses of climate variables such as precipitation and temperature. Drought is clearly a consequence of climate anomalies, as well as of human water use practices, but many impacts to society are more directly related to hydrologic conditions resulting from these two factors. Modern hydrology models can provide a valuable counterpart to existing climate-based drought indices by simulating hydrologic variables such as land surface runoff. We contrast the behavior of a standardized runoff index (SRI) with that of the well-known standardized precipitation index (SPI) during drought events in a snowmelt region. Although the SRI and SPI are similar when based on long accumulation periods, the SRI incorporates hydrologic processes that determine seasonal lags in the influence of climate on streamflow. As a result, on monthly to seasonal time scales, the SRI is a useful complement to the SPI for depicting hydrologic aspects of drought. **Citation:** Shukla, S., and A. W. Wood (2008), Use of a standardized runoff index for characterizing hydrologic drought, *Geophys. Res. Lett.*, *35*, L02405, doi:10.1029/2007GL032487.

1. Motivation

[2] Drought is a multi-faceted phenomenon that occurs across a range of temporal and spatial scales and is experienced across a range of societal sectors that are dependent on climate and water resources [*Wilhite*, 2000]. Many indicators used to describe drought are derived from analyses of climate variables such as precipitation and temperature. The impacts of drought are a consequence of climate anomalies, as well as of human water use practices, but many impacts are more directly related to the resulting hydrologic conditions. Several drought indices attempt to incorporate the interaction of the land surface with climate, including, e.g., the Palmer Drought Severity Index (PDSI) [*Palmer*, 1965], but the conceptual moisture accounting of the PDSI (and related indices) represents evaporative effects crudely and omits snow accumulation and melt entirely [*Alley*, 1984]. Others, such as the Standardized Precipitation Index (SPI) [*McKee et al.*, 1993] are purely related to climate. Soil moisture is also recognized as an important indicator of drought for agriculture and other sectors. The National Oceanic and Atmospheric Administration (NOAA) Climate Prediction center (CPC), for example, uses a simplified water balance model [*Huang et al.*, 1996] to simulate soil moisture percentiles for drought monitoring in the United States (US). The current state-of-the-practice drought analysis in the US, the US Drought Monitor (USDM) [*Svoboda et al.*, 2002], is subjectively assembled from estimates of climate indices such as the PDSI, SPI, streamflow percentiles, snow water equivalent (SWE) anomalies, CPC soil moisture percentiles, and various other minor inputs.

[3] The potential to advance the hydrologic basis for drought monitoring now exists. The last decade has seen the maturation of a class of macro-scale hydrology models that incorporate sufficient physics to maintain water and energy balances of the major components of the top 1–2 meters of the land surface, operate at between an hourly and daily timestep, and run at horizontal grid resolutions that are far finer than the climate division and even county level data sources of the USDM. Foremost among the modeling efforts in the US is the NOAA Land Data Assimilation Project (NLDAS) [*Mitchell et al.*, 2004], which has helped to promote the development and calibration of four land surface schemes over much of North America at 1/8 degree spatial resolution.

[4] These models produce real-time modeled soil moisture, SWE and runoff estimates at sub-daily time steps. We focus here on runoff, a primary concern to water managers, because it is closer to being a verified product from models than soil moisture. The drought monitoring and management community widely uses data expressed in an index framework. We also employ an index framework to demonstrate the application of modeled runoff for water cycle analysis in the context of drought.

2. Hydrologic Modeling

[5] We use the physically based, semi-distributed macro-scale Variable Infiltration Capacity (VIC) model [*Liang et al.*, 1994] to simulate the land surface water balance. Like other NLDAS project models, VIC accounts for modulation by vegetation of land-atmosphere moisture and energy fluxes, and attempts to represent sub-grid variability of vegetation, soil and terrain characteristics via sub-grid area-specific parameter classifications and an infiltration algorithm that involves the areal extent of soil saturation. Soil layer depths, infiltration and base flow parameters are adjusted during model calibration, the primary goal of which is often to reproduce observed streamflow.

[6] The VIC model has been applied for analyzing historical drought events for the entire U.S. [*Andreadis et al.*, 2005] and globally [e.g., *Sheffield and Wood*, 2008]. We draw here on VIC model results from the 1/8 degree implementation for the Feather R. basin, California, described by *Wood and Schaake* [2008], and on the $^1/_2$ degree continental

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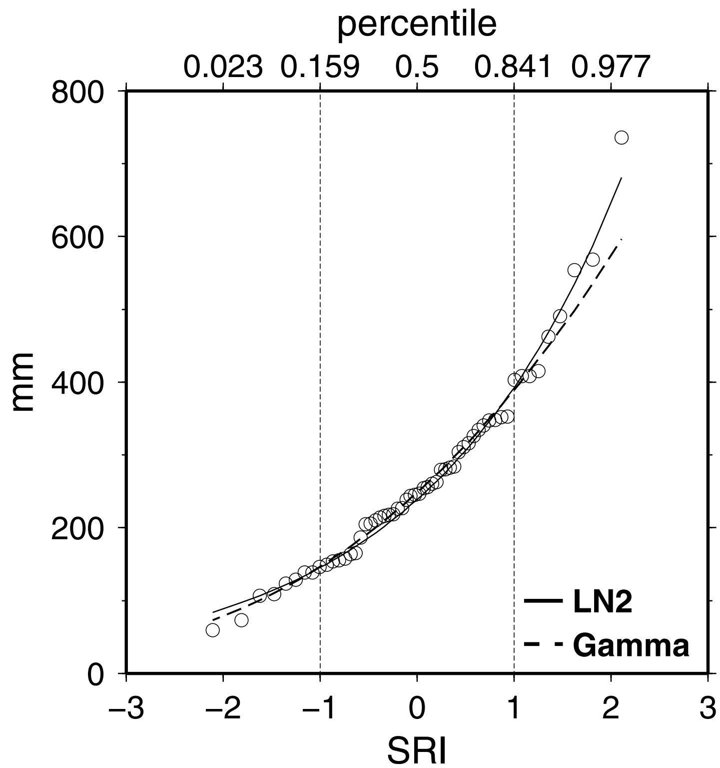

Figure 1. The simulated historical (1955 to 2005) distribution of 3-month runoff (areal average depth) accumulations for March, April and May in the Feather River basin. The sample is fitted with Gamma and Log Normal (LN2) distributions. The SRI (bottom axis) is the unit standard normal deviate associated with the percentiles of the runoff value (top axis).

US (CONUS) implementation [*Andreadis et al.*, 2005] that is incorporated in the real-time University of Washington Surface Water Monitor (see http://www.hydro.washington.edu/forecast/monitor/). Both models use gridded NOAA National Climatic Data Center Cooperator station precipitation, temperature minima and maxima as inputs to simulate the water balance at a daily time step. Typical outputs include daily surface runoff, baseflow, evaporation, soil moisture and SWE for each grid cell. We sum daily surface runoff and baseflow from each cell together to form, simply, "runoff", and temporally average runoff to form monthly totals for each model grid cell. At large spatial scales, this runoff differs from streamflow because it is not routed through a channel network.

3. Standardized Runoff Index

[7] We apply the concept employed by *McKee et al.* [1993] for the SPI in defining a standardized runoff index (SRI) as the unit standard normal deviate associated with the percentile of hydrologic runoff accumulated over a specific duration. Different durations (e.g., 1-month, 9-month) and different spatial aggregations of the index can be calculated depending on source data resolution and desired application. SPIs, for instance, are calculated by NOAA on a climate division basis and by state agencies on a county level basis. The procedure for calculating the SRI includes the following steps: (1) A retrospective time series of runoff is obtained by simulation, and a probability distribution is fit to the sample represented by the time series values. (2) The distribution is used to estimate the cumulative probability of the runoff value of interest (either the current accumulation or one from a retrospective date). (3) The cumulative probability is converted to a standard normal deviate (with zero mean and unit variance), which can either be calculated from a numerical approximation to the normal cumulative distribution function (CDF) or extracted from a table of values for the normal CDF that is readily available in statistics textbooks or on the World Wide Web.

[8] *McKee et al.* [1993] select the Gamma distribution for fitting monthly precipitation data series, and suggest that the procedure can be applied to other variables relevant to drought, e.g., streamflow or reservoir contents. In pursuing this suggestion for model-based runoff, we note that distributions other than the Gamma may be more appropriate, depending on the runoff variable's retrospective sample characteristics (especially skew and kurtosis), which vary greatly by geographic location and degree of temporal aggregation. Figure 1, showing the distribution of areal average 3-month total simulated runoff during March, April and May from the years 1955–2005 for the Feather River basin, California, makes clear that any value of runoff can equally well be expressed in terms of its percentile (top axis) or the standardized index (bottom axis). Here the 2 parameter log normal (LN) distribution, for example, provides a better fit at high extremes than the Gamma distri-

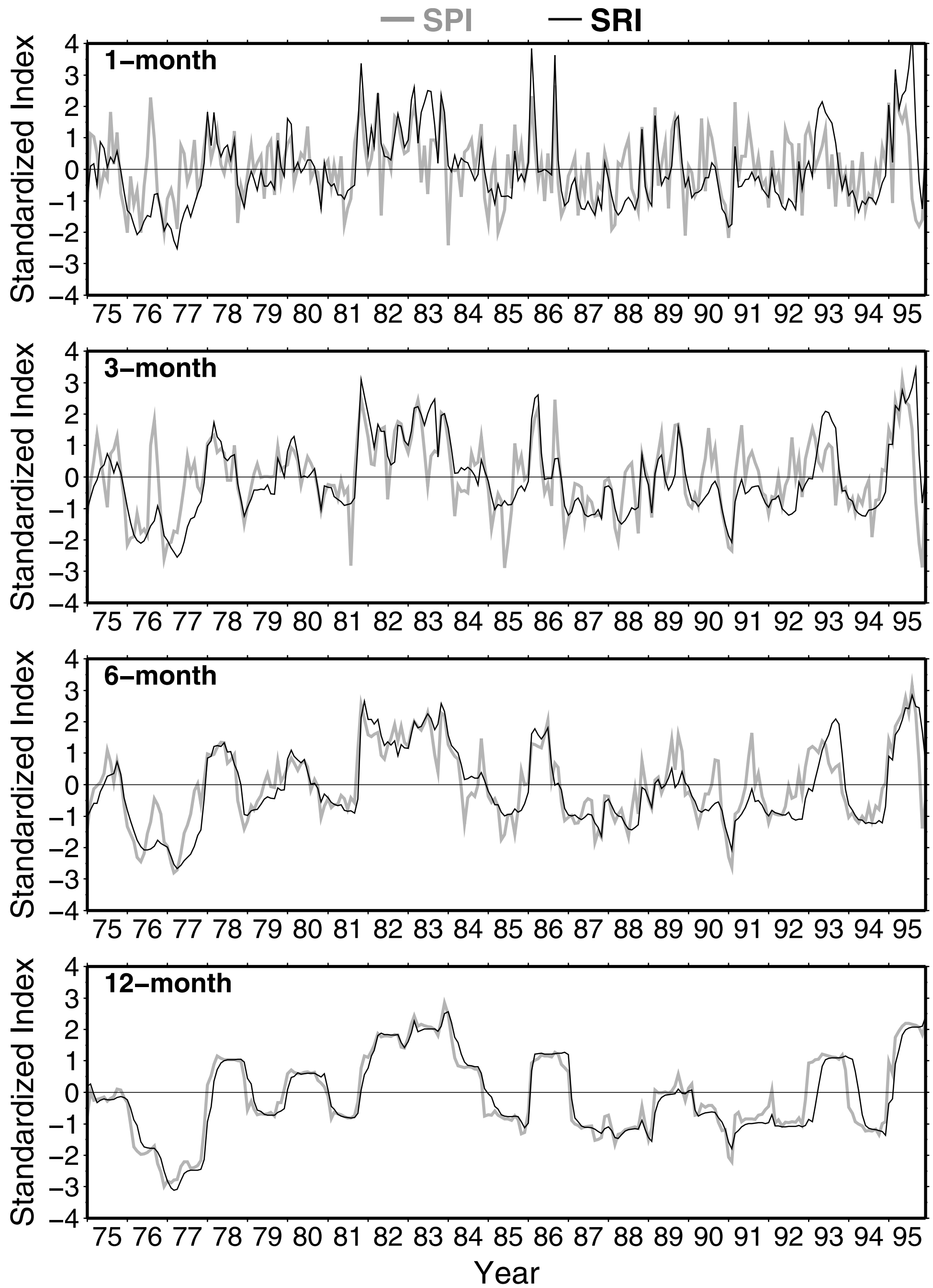

Figure 2. Historical time series of the SPI and SRI for 1-, 3-, 6- and 12-month accumulation periods, based on observed precipitation and simulated runoff in the Feather River basin.

bution whereas the Gamma distribution may perform better for low runoff values. The 3-parameter LN and Generalized Extreme Value distributions may have even better general applicability for runoff over widely varying hydro-climatic regimes. Where a satisfactory distribution fit cannot be achieved, an alternative is to estimate percentiles empirically. Care must be taken to negotiate the first two steps above so as to minimize errors in estimating the probability of runoff, particularly in arid regions where runoff may be intermittent. Note that SRI units are non-linearly related to percentiles, so a change in SRI from −2 to −3 equals a smaller percentile change than an SRI change from 0 to 1. This correspondence is common to other USDM indices, reflecting the non-linear relationship of drought severity to the probability of a drought event.

4. Results

[9] We illustrate differences in the behavior of the SPI and SRI using areal averages of observed precipitation and simulated runoff in the Feather River basin. Figure 2 shows monthly time series of the indices for four accumulation

periods (1-, 3-, 6- and 12-month) for the years 1975–1995. The 12-month SPI and SRI are very similar due to the high correlation between annual precipitation and runoff (r = 0.9). The differences between the indices increase as the accumulation period decreases, with SPI to SRI correlations dropping from 0.88 for the 12-month period to 0.82, 0.69 and 0.01 for the 6-, 3-, and 1-month period indices. For shorter period accumulations, the SRI is less variable from month to month than the SPI due to the detention of moisture in snow or soil storages that regulate runoff. Figure S1 shows the autocorrelation of 1-month runoff provided by these storages at different times of the year.[1] The 12-month indices integrate over an entire water year, longer than most effects of hydrologic modulation. A long integration, however, accumulates values that are well past and that may no longer influence current land surface conditions. For example, a large event in early 1986 causes the 12-month indices to remain above 1.0 for 2 months after the 1- and 3-month SRIs fall below values of −1.0, in December, 1986.

[10] The 1976–1977 and 1987–1992 California drought events are evident in all four sets of timeseries, as is the 1995 flood year. During the drought years, the 12-month indices are both negative, with the exception of a few months in 1989. These results compare well qualitatively to recorded precipitation and runoff anomalies for Sacramento River basin, which contains the Feather River basin: percentages of normal during each of the six years were, respectively, 55, 75, 100, 75, 75, 76 for precipitation and 49, 49, 78, 49, 45, 47 for runoff [*Dziegielewski et al.*, 1993]. During drought events, the shorter period indices attain positive values more frequently than the 12-month indices and the SPI recovers to above normal levels more frequently than the SRI. In 1990–1991, the SPI describes spells of precipitation that are insufficient to ameliorate hydrologic drought conditions, a reality reflected in the non-recovery of the SRI at these times. In winter 1992–1993, however, the SPI increase corresponds to a building snowpack, and presages a recovery from drought; whereas the SRI reflects only current runoff and remains low until the snowmelt period arrives. In this case, unlike the SRI, the SPI has predictive value.

[11] The hydrologic importance of precipitation varies greatly depending on the seasonal precipitation climatology and the current land surface moisture state. Figure 3 shows the 3-month SPI and SRI values for the Feather R. basin together with daily basin areal averages of observed accumulated water year precipitation and simulated soil moisture, SWE and water year runoff for the drought year of 1991 and the flood year of 1995. In 1991, recorded precipitation in March was 300 percent of average, which is evident in the step change in accumulated precipitation, soil moisture and runoff, increases in SWE, and return to above normal of the 3-month SPI. The recharge of low soil moisture, however, diminishes runoff, muting the SRI recovery. Qualitatively, these dynamics are corroborated by reports of *Dziegielewski et al.* [1993, p. 70]: "Since the onset of drought in 1987, California has experienced at least one month of above-normal precipitation during each water year...However, these precipitation 'bursts' were not adequate to overcome water shortages in most parts of the state accumulated during the previous months of the respective water years."

[12] A contrasting hydrologic situation is given by the extreme precipitation events in January and March 1995, which together caused flooding that claimed 28 lives and led to over $220 million in damages [*The Resources Agency*, 2003]. As Figure 3 shows, these storms arrived when soil moisture was near or above normal, and drove increases in SWE, runoff and consequently both SPI and SRI to much above normal. Below average summer precipitation then caused SPI to plummet. Precipitation during California's relatively dry summers, however, often contributes less to summer runoff than the moisture accumulated in the soil and SWE during winter. In 1995, the summer precipitation deficits were greatly overshadowed by the discharge of stored moisture, hence runoff and the SRI remained high through the end of the water year.

[13] Due to hydrologic delays in the form of snow and soil moisture, the SPI may be desynchronized from response of the land surface to those anomalies (the USDM, partly for this reason, advises caution in interpreting short duration SPIs) – whereas the SRI incorporates the land surface dynamics that moderate the hydrologic response. Snow-free regions lack the delay due to snow accumulation (longer than soil storage delay), hence the SPI and SRI are better correlated at short durations, despite the SRI's attenuation of the precipitation signal. Figures S2 and S3 duplicate Figures 2 and 3 for a snow-free location.

5. Operational Mapping of Runoff on Continental Scales

[14] The land surface modeling activities noted in section 1 are capable of producing runoff and derived indices such as the SRI on a continental scale, using multiple hydrologic models, for both current and projected conditions (e.g., based on climate predictions from CPC). Figure 4, for example, shows a real-time SRI analysis based on the $^1\!/_2$ degree VIC model simulation (section 2)] for 3-month runoff conditions as of September 2007. In general, the locations of wet and dry conditions across the domain are represented similarly by the SPI and SRI. The SRI is higher than the SPI in Oklahoma and Texas due to surplus moisture remaining from extreme summer 2007 flooding, and is lower in the western US where the water year was much drier than average. In California, the 3-month SPI is above normal, in contrast to the SRI and to the 2007-09-25 USDM, which depicted all counties as being at least "Abnormally Dry". The recent extension of NLDAS retrospective simulations back to 1979 is long enough estimate runoff distributions, despite post-dating important prior drought events (e.g., 1976–77, the Dust Bowl). The potential value of hydrologic anomaly products that depend on the existence of consistent historical analyses argues that the NLDAS extension should be a stepping stone toward even longer retrospective simulations.

6. Conclusions

[15] The foregoing examples demonstrate that modeled runoff could provide a useful counterpart to climate-based

[1]Auxiliary materials are available in the HTML. doi:10.1029/2007GL032487.

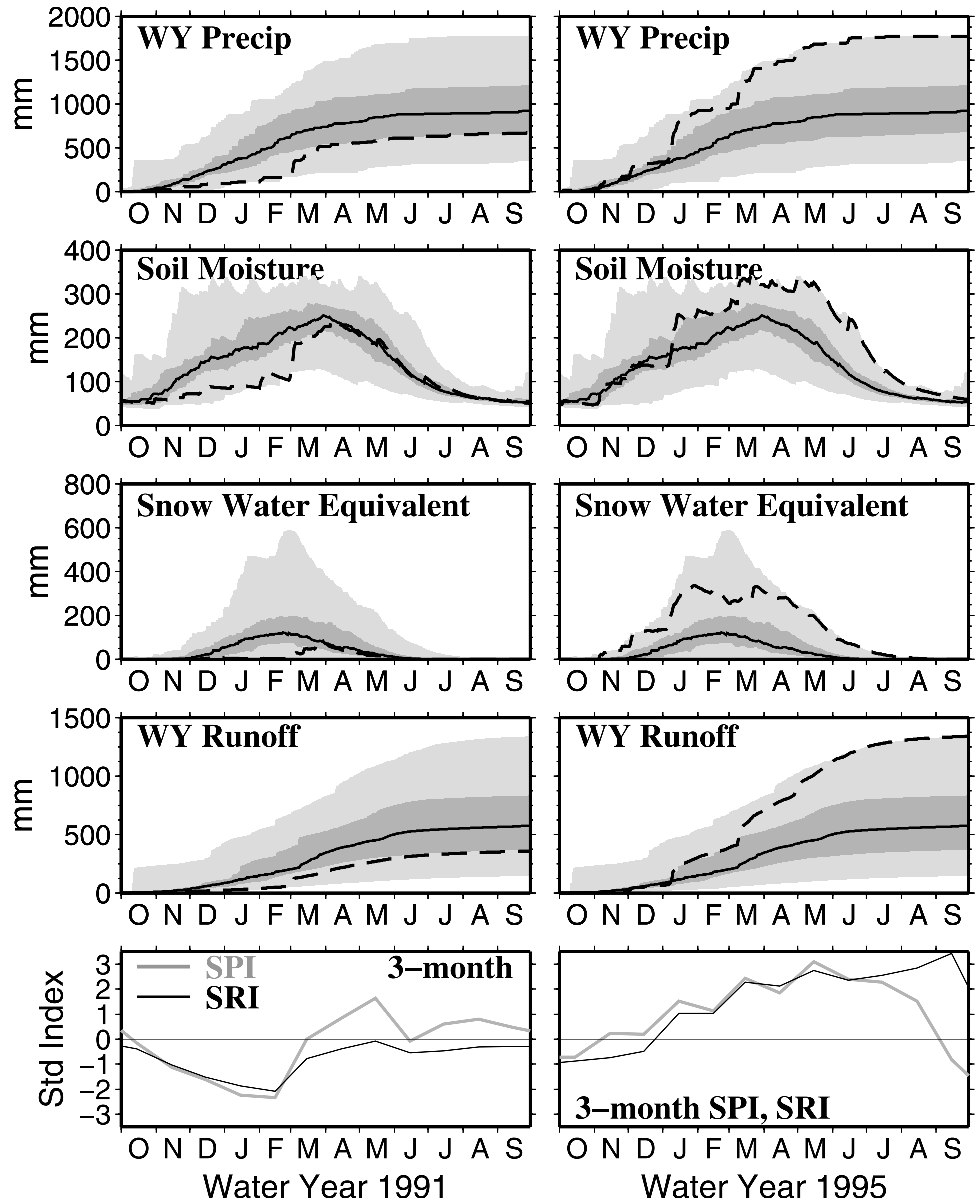

Figure 3. The Feather River basin areal average water balance during two water years ((left) 1991 and (right) 1995) compared with the 3-month SPI and SRI. Daily values of observed precipitation and simulated soil moisture, snow water equivalent and runoff in each of the two years (dashed line) are plotted against the minimum, maximum, and quartiles of their daily historical distribution from 1955 to 2005. The SPI and SRI have a monthly time step.

indices for drought monitoring and management. Due to the popularity of the SPI, the multi-period SRI framework for runoff is likely to be familiar to the drought research, monitoring and management communities. Whereas climate-based indices describe the climate anomalies in isolation from their hydrologic context, hydrologic indices directly describe the effects of climate anomalies on current hydrologic conditions as governed by land surface physical processes. One strength of a runoff-based index is that it can be forecast, and its predictability depends not only on climate outlooks, for which seasonal skill is generally low, but on hydrologic initial conditions, which in some seasons largely determine future runoff (e.g., spring snow state in the western US). A second strength is that calibrated runoff simulations are more widely available for real-time application than naturalized (e.g., adjusted to remove human impairments) streamflow observations, which precludes the use of streamflow in a real-time framework [e.g., *Modarres*, 2007] in most locations. Modeled runoff cannot be verified everywhere, however, thus runoff-based indices such as the SRI reflect the customary uncertainties associated with model outputs. Nevertheless, model-based hydrologic runoff (in index form or otherwise) shows potential to complement existing climate indices and local hydro-climatological information (e.g., knowledge of when/where snow accumulation is occurring), leading to improvements in the assessment of current and future drought status.

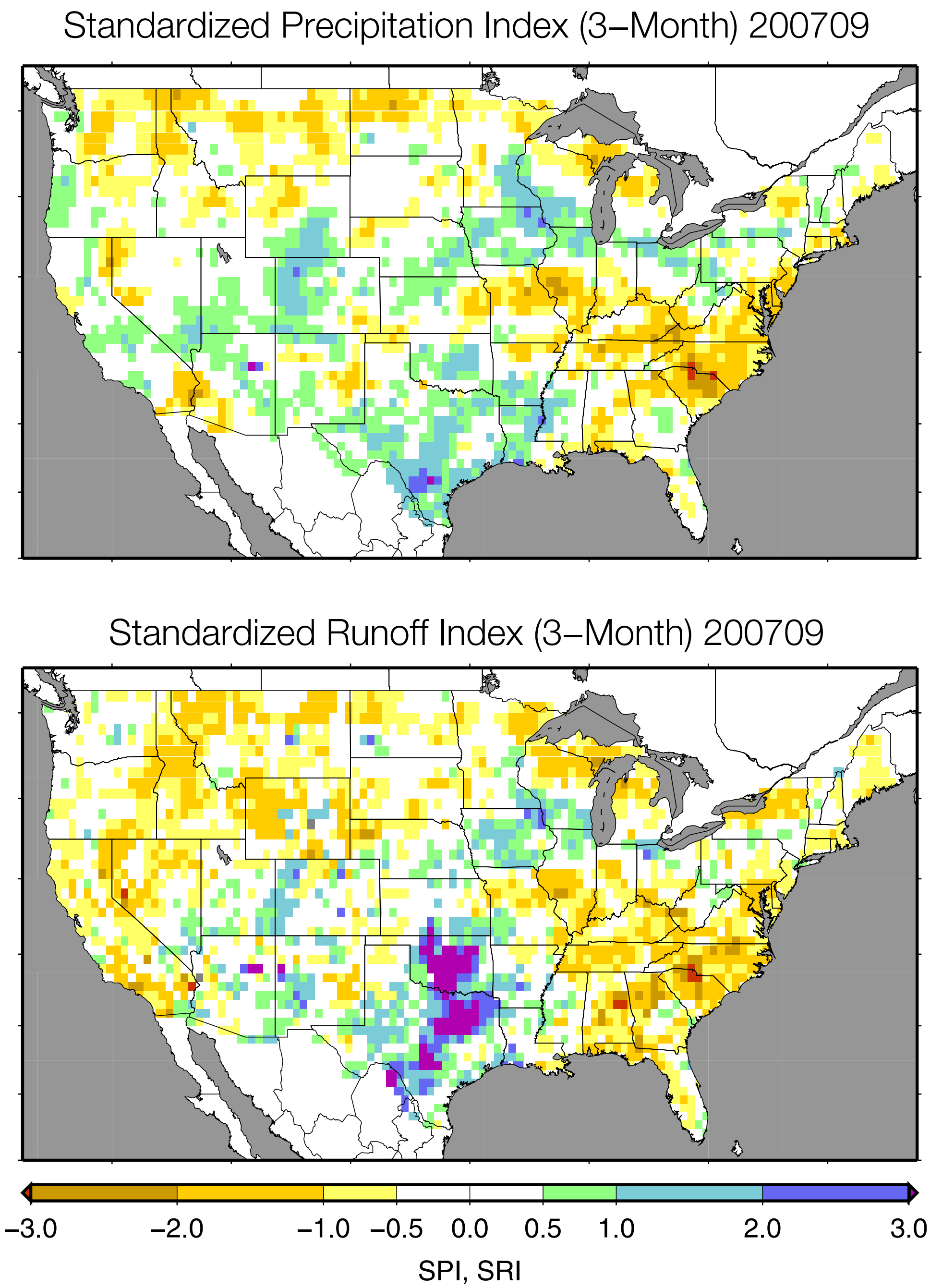

Figure 4. The 3-month SPI and SRI for September 2007 as calculated from observed precipitation and simulated runoff on a $^1/_2$ degree grid.

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