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Comment on "Characteristics and trends in various forms of the Palmer Drought Severity Index (PDSI) during 1900–2008" by Aiguo Dai

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1. Introduction

[1] *Dai* [2011] (henceforth D11) reported that the Palmer Drought Severity Index (PDSI) is superior to other statistically based drought indices including the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI). D11 argued that given the physical character of the PDSI water balance model, the index provides robust estimates of drought severity because it takes the preceding conditions into account, in contrast to other drought indices that are based purely on past statistics of particular climate variable(s). However, D11 has overestimated the ability of the PDSI to realistically simulate the distributed soil water balance at large spatial scales, and ignored the inherent complexity and multiscalar character of drought phenomena, which are related to more than the moisture conditions of the soil. In this comment we discuss the complex characteristics of droughts and the limitations of the PDSI to quantify drought conditions in a variety of hydrological systems. We describe the advantages of statistically based drought indices including the SPI and the SPEI. The fact that the SPI and the SPEI are not (and do not intend to be) physically based indices is more liberating than constraining, especially when the physical basis of PDSI can be seriously questioned.

[2] Drought is a complex phenomenon that involves both human and natural factors. In contrast to other extreme events such as floods, which are typically restricted to small regions and well defined temporal intervals, droughts are difficult to pinpoint in time and space, and affect large areas over long periods of time. It is very difficult to identify the moment when a drought starts and finishes, and to quantify its duration, magnitude and spatial extent [*Burton et al.*, 1978; *Wilhite*, 2000]. For these reasons substantial efforts have been devoted to developing methods to quantify drought severity. The main efforts have been directed at developing drought indices that enable earlier identification of droughts, and quantification of their severity and spatial extent. Several drought indices were developed during the 20th Century, based on a range of variables and parameters (see reviews by *Heim* [2002], *Keyantash and Dracup* [2002], *Mishra and Singh* [2010], and *Sivakumar et al.* [2010]). Thus, drought indices have become very important for monitoring drought continuously in time and space, and drought early warning systems are based primarily on the information that drought indices provide [*Svoboda et al.*, 2002].

[3] D11 analyzed the spatial and temporal patterns of drought variability and drought trends at a global scale using the Palmer Drought Severity Index (PDSI) under different modalities (original and self-calibrated; sc) and using two different models to calculate the potential evapotranspiration as input to the Penmann-Montheith and Thornthwaite model. Global studies including D11 are central to obtaining a deep understanding of changes in drought severity, the associated atmospheric mechanisms, and the possible impacts on surface hydrology, water resources, agriculture and ecology.

[4] D11 noted that the PDSI is a physically based water balance model and stated that it is superior to other statistically based drought indices because it accounts for the basic effect of global warming through Palmer's water balance model of droughts and wet periods. D11 questioned the applicability of drought indices that are based on the statistical characteristics of particular climate variables. He specifically drew attention to the Standardized Precipitation Evapotranspiration Index (SPEI) [*Vicente-Serrano et al.*, 2010a], critically noting that it is based on potential evapotranspiration (PE) and not on actual evapotranspiration (E). The rationale was that it is E and not PE that determines the surface water balance and the drought conditions. It was argued that because PE and E are often decoupled (or even anti-correlated) over many water limited land areas where drought studies are most relevant, a physical model is necessary to calculate the moisture condition near the surface, from which a drought index should be derived.

[5] We discuss here shortcomings of the PDSI in adequately modeling the soil water balance, and its limited ability to quantify and monitor droughts of different types. Conversely, we describe the advantages of statistically based drought indices in analyzing the spatial and temporal variability of drought, identifying drought impacts in a

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variety of systems, and monitoring drought conditions in real time.

2. Limitations of the PDSI as a Soil Water Balance Model

[6] It is widely recognized that the PDSI has numerous deficiencies [e.g., *Alley*, 1984]. *Karl* [1986] showed that the PDSI is highly affected by the selected calibration period. In addition, the parameters necessary to calculate the PDSI were determined empirically and mainly tested in the U.S.A., which restricts its use in other regions [see *Akinremi et al.*, 1996]. It has been shown that the PDSI is not spatially comparable because the weighted factors were obtained from data for nine climatic divisions in the U.S.A., which were aggregated at an annual level [*Heim*, 2002]. *Guttman et al.* [1992] illustrated that severe or extreme drought events recorded by the PDSI are not spatially comparable, as the cumulative frequencies of the index vary spatially [*Karl et al.*, 1987; *Nkemdirim and Weber*, 1999]. *Redmond* [2002] noted that the creator of the PDSI, W.C. Palmer, did not intend or foresee significant use of the index beyond the Great Plains, in the central U.S.A. Other problems with the PDSI have been reported. *Karl* [1983] analyzed the sensitivity of the PDSI to the water field capacity parameter, and reported that areas of greater capacity are more likely to be affected by drought, in agreement with the findings of *Weber and Nkemdirim* [1998]. *Alley* [1984] also noted subjectivity of the PDSI in terms of assigning real drought conditions to the values of the index.

[7] Despite problems with the PDSI, its creation in 1965 was a major landmark in the development of drought indices, and it has been very useful in monitoring and analyzing drought variability and impacts worldwide. Improvements to the PDSI by *Wells et al.* [2004], who developed the self-calibrated PDSI (sc-PDSI), solved most of the problems of calibration of the PDSI, making the index more suitable for drought quantification and monitoring.

[8] Although the PDSI is commonly cited as a physically based soil water balance, as it considers the soil water capacity, precipitation and outputs in the form of evapotranspiration, infiltration and/or runoff, the procedure for its calculation is based on several assumptions and simplifications. Claims, such as those of D11, that the PDSI is a physically based soil water balance have been questioned by many drought researchers [e.g., *Sheffield et al.*, 2004].

[9] Many believe that the soil water balance cannot be accurately simulated using only climatic data and the soil water capacity, while completely neglecting other soil properties and the complex role of vegetation in the calculation of E. In practice, the PDSI cannot be considered a robust water balance model as it oversimplifies soil surface hydrological processes. The best way of obtaining accurate soil water balance calculations is by using highly complex physically based hydrological models such as TOPMODEL [*Beven*, 1997], TOPKAPI [*Ciarapica and Todini*, 2002], or RHESSys [*Tague and Band*, 2004]. Moreover, soil-moisture estimations are very complex and model dependent [*Mo*, 2008], which makes the multimodel soil moisture estimates more confident than using just a single model [*Wang et al.*, 2009]. State-of-the-art models including the above typically require a high degree of parameterization to provide accurate estimates of the soil water balance, and its horizontal and vertical distribution over a catchment. The parameters include the soil saturated hydraulic conductivity and porosity, factors that influence the water balance (including topography, surface roughness), and the physiological and phenological characteristics of the vegetation. In contrast, the PDSI only requires the water field capacity.

[10] Despite the parsimony of the PDSI, available information on soil water capacity is very poor; this has led to the use of inaccurate values when applying the PDSI in most regions of the world. Therefore, the PDSI is affected by both model uncertainty and the propagation of input data errors. Because of over-simplification of soil water processes in the PDSI, it has been reported that climatic components (precipitation and potential evapotranspiration) explain most of the spatial and temporal variability of the index. This explains why numerous reports have been made of strong correlations of the PDSI with the SPI and SPEI at various time-scales [e.g., *Guttman*, 1998; *Redmond*, 2002; *Ntale and Gan*, 2003; *Ceglar and Kajfež-Bogataj*, 2008; *Vicente-Serrano et al.*, 2010b], which show that the PDSI behaves more as a climatic drought index than a measure of soil water balance.

[11] It is important to appreciate that E, which is a very difficult variable to measure, cannot be accurately computed using a simplistic water balance model like the PDSI. Although specific instrumentation (e.g., lysimeters and eddy-covariance towers) is available, the measurements are usually highly dependent on very specific characteristics of the plant cover (e.g., type of vegetation, root depth, sap flow, stomatal conductance), and the strategies and efficiency of vegetation physiological mechanisms to cope with water stress [*McDowell et al.*, 2008]. Therefore, the reliability of estimates of E at regional scales, only using climate data, is quite low. The calculation of distributed E values is commonly based on remote sensing data because it accounts for the vegetation cover and type, which are the main variables involved in the determination of E [e.g., *Bastiaanssen et al.*, 1998; *Jacob et al.*, 2002; *Zhang et al.*, 2010]. Although some models combining climatic, hydrological and plant physiology information have been proposed to provide estimates of E, their use is limited because of the high degree of uncertainty in the simulation of water consumption by vegetation [e.g., *Choudhury and DiGirolamo*, 1998; *Morales et al.*, 2005; *Alton et al.*, 2009]. In addition, even with application of the most complex procedures the models typically consider vegetation cover to be static, and do not incorporate vegetation cover changes, which are common and can occur abruptly (deforestation, forest fires, reforestation, desertification, irrigation), markedly affecting the magnitude of E.

[12] Given the difficulties in accurately estimating E, an operative way to incorporate the effect of evaporative demand on drought indices is to use an estimate of the potential evapotranspiration (PET) from empirical or physical models. Such methods have been widely accepted by the International Commission for Irrigation (ICID), the Food and Agriculture Organization of the United Nations (FAO), and the American Society of Civil Engineers (ASCE). This is the approach commonly used when drought indices are calculated [*Heim*, 2002; *Sivakumar et al.*, 2010], and the one we followed in developing the SPEI. We consider that using PE instead E is a reliable way of quantifying the influence of evapotranspiration processes on the availability of water resources in a variety of systems (and not only in the soil, as is the case with the PDSI).

[13] It has been argued that unrealistic water balances are obtained when PE is used instead of E. This is especially the case when PE exceeds the water available in the soil, which limits the evapotranspiration rate. This would be a major shortcoming of the SPEI if the index was aimed at estimating the soil water balance, but this is not its purpose. On the contrary, the SPEI is defined in a relative way (in standardized units), and consequently the magnitude of PE is not relevant even if the difference between precipitation and potential evapotranspiration (P–PE) is negative. In other words, the SPEI measures deviations with respect to normal conditions of P-PE, and therefore the magnitude of this balance is of less importance. We see this as an advantage rather than a shortcoming. In fact, in using the PDSI it is assumed that when the soil water content is close to zero the magnitude of PE does not have an effect on the magnitude of drought. It could be argued, however, that increasing evapotranspiration demand when the soil water reserve is already minimal could have a very negative impact on plants. In other drought-vulnerable systems including surface water resources (rivers, lakes and reservoirs), it is known that increasing PE affects water loss by direct evaporation [*Hostetler and Bartlein*, 1990; *Elsawwaf et al.*, 2010]. The widely analyzed 2003 and 2010 summer droughts in Europe are excellent examples of how, independently of the available soil moisture, increased PE rates as a consequence of extremely high temperatures have a marked impact on vegetation activity, and in this case led to tree mortality and wild fires [*Ciais et al.*, 2005; *Lobo and Maisongrande*, 2006; *Granier et al.*, 2007; *Barriopedro et al.*, 2011]. Therefore, we consider that the use of PE estimates in the calculation of a drought index is very useful, has a theoretical justification, and it is an efficient and easy way to include the effect of evapotranspiration demand on a variety of systems.

[14] In contrast to the PDSI, which aims to model the water balance at the soil level, indices including the Standardized Precipitation Index (SPI) and the SPEI are purely statistical, and are not intended to reproduce the water balance of any particular system. The advantages of such indices are that: i) their calculation only requires climatological information, which is often available and of reasonable quality; ii) they do not require any assumptions about the system being modeled; and iii) they compute the climatological anomalies for periods of exact length (termed the 'time scale' of the index). In our opinion the fact that they are not physically based is more liberating than constraining. The ability to calculate these indices at various time scales allows choice of the scale most appropriate to the system under study, and can be achieved using simple statistics such as correlation analysis.

3. The Inability of the PDSI to Quantify Droughts on Different Time Scales

[15] One reason one cannot say that the PDSI is superior to the SPI and the SPEI is mainly because it lacks flexibility to adapt to the intrinsic multiscalar nature of drought. In recent years the concept of time scales has been widely used by drought scientists, and it is explained in several reports (e.g., the pioneer studies by *McKee et al.* [1993, 1995] or *Hayes et al.* [1999]). When the SPEI was enunciated the need for monitoring and analysis of droughts at different time scales had been broadly accepted by the scientific community, as highlighted by *Vicente-Serrano et al.* [2010a, p. 1697]:

> It is commonly accepted that drought is a multi-scalar phenomenon. McKee et al. (1993) clearly illustrated this essential characteristic of droughts through consideration of usable water resources including soil moisture, ground water, snowpack, river discharges, and reservoir storages. The time period from the arrival of water inputs to availability of a given usable resource differs considerably. Thus, the time scale over which water deficits accumulate becomes extremely important, and functionally separates hydrological, environmental, agricultural and other droughts. For example, the response of hydrological systems to precipitation can vary markedly as a function of time… This is determined by the different frequencies of hydrologic/climatic variables… For this reason, drought indices must be associated with a specific timescale to be useful for monitoring and management of different usable water resources.

[16] Thus, it is common to find drought conditions in a hydrological system, whereas other systems in the same region may have normal or even humid conditions. As a simple and illustrative example, three months without precipitation will commonly produce drought conditions with respect to the soil moisture. Nevertheless, this lack of precipitation probably will not have an effect on the discharge of large river systems, or in the level of water stored in the reservoirs of a region. The contrary pattern also commonly occurs. For example, four years of low precipitation will probably produce a severe hydrological drought in terms of river discharge and reservoir storages, but during the drought period high precipitation events may produce high levels of soil moisture. Thus, it is common for drought conditions to occur in only a part of the hydrological cycle. The problem is even more complex when the various systems affected by droughts are considered (hydrological, agricultural, environmental, socioeconomic), as the response times to water deficits and the resistance of each system to drought can vary substantially. The complexity of drought makes more suitable the use of drought indices, such as the SPI or the SPEI, that can be calculated on different time scales.

[17] Numerous scientific studies have shown that particular systems and regions can respond to drought conditions at very different time scales. In terms of water resources, *Vicente-Serrano and López-Moreno* [2005] used the SPI to show that the response of river discharges and reservoir storages to different drought time scales in mountainous catchments can be diverse (1–2 months for river discharges and 8–10 for reservoir storages). *Szalai et al.* [2000] also showed that water stored in reservoirs in Hungary responded to longer time scales (5 to 24 months) than streamflows (2 to 6 months). The same is observed using groundwater data [e.g., *Fiorillo and Guadagno*, 2010; *Vidal et al.*, 2010]. Nevertheless, the spatial diversity is very high, and the hydrological system of one region may respond very differently to that in another region, as a consequence of lithology, topography or the water management regime. This has been observed for soil moisture data [*Mo*, 2008; *Mishra et al.*, 2010; *Mishra and Cherkauer*, 2010] but also for streamflows and reservoir storages. For example, in a study in the headwaters of the Tagus basin (central Spain) using the SPEI, *Lorenzo-Lacruz et al.* [2010] showed that the 8-month SPEI most accurately reflected the streamflow but reservoir stora-

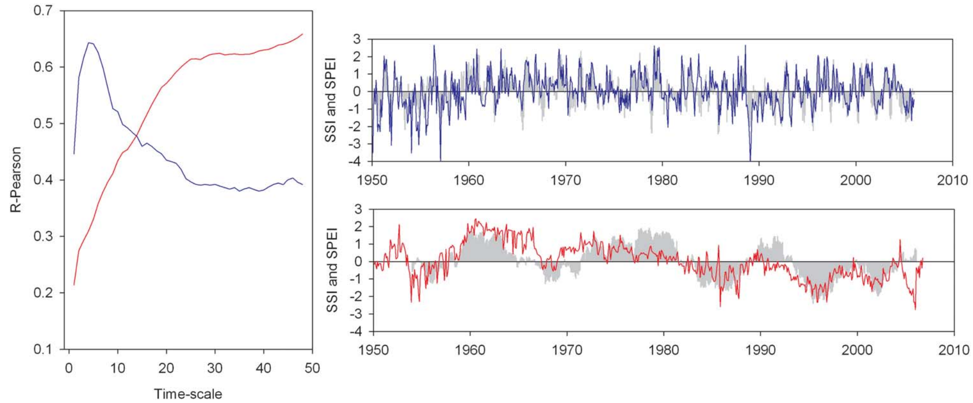

Figure 1. (left) Correlation between the Standardized Streamflow Index (SSI) and the SPEI at different time scales; blue: Gallego River, red: Jiloca River. (right) Evolution of the SSI (blue and red lines) and (top) the 4-month SPEI (gray) and (bottom) the 48-month SPEI (gray).

ges showed a response to 33-month SPEI; these time scales are much longer than those observed in other regions. *Szalai et al.* [2000] also reported large spatial differences in the time scales that occur for reservoir storages in Hungary. Similarly, *Khan et al.* [2008] analyzed fluctuations in the level of the water table in different basins in Australia, and related these to varying time scales of droughts. Large spatial diversity in response was found, with some basins showing a clear response at the 6-month time scale, but for others the highest correlation was found at time scales of 12–24 months. The problem is even more complex because the relationships can change over time and may exhibit large seasonal variability [*Vicente-Serrano and López-Moreno*, 2005; *Lorenzo-Lacruz et al.*, 2010].

[18] As an example of the diversity that commonly occurs in the response of water resources to drought time scales, we showed the evolution of a hydrological drought index (the Standardized Streamflow Index, SSI [*Vicente-Serrano et al.*, 2011]) at two gauging stations of the Ebro basin (northeast Spain), and its relationship to different time scales of the SPEI (Figure 1). The Gallego River, which is located in a granitic mountainous area, is strongly correlated at short time scales (maximum correlation at 4 months). In contrast, the Jiloca River, which is located in a karst area, shows a very low inertia in the streamflows and strong correlation to long time scales (maximum at 48 months). Therefore, if the PDSI were used to monitor droughts in these basins the sensitivity of streamflow would be low, as the time scales represented by the PDSI (9–18 months [*Vicente-Serrano et al.*, 2010b]) would show weak correlations for the two rivers analyzed.

[19] Despite the above discussion it could be argued that the PDSI is useful for the analysis of hydrological droughts because it is significantly correlated to streamflow. For example, D11 records a correlation between the annual PDSI and annual streamflow in 230 basins worldwide. Nevertheless, drought indices including the PDSI and the SPEI were not designed to monitor streamflow droughts at an annual scale. For this purpose raw climate variables, such as annual precipitation, should provide similar results considering annual averages. Using the same analysis as D11 we assessed the relationship of total water-year streamflow in 151 basins from the global data set of *Dai et al.* [2009] to total annual precipitation, average annual PDSI and the 12-month SPEI. The 151 basins were selected based on the percentage of complete records in the original data set (maximum of 15% of filled monthly records). The monthly average precipitation and temperature of each basin, obtained from the Climate Research Unit (CRU) TS 3.1 Data set [*Mitchell and Jones*, 2005] was used to determine the sc-PDSI and the SPEI. The PE values necessary to derive both indices were calculated by the Thornthwaite method [*Thornthwaite*, 1948], which is the simplest procedure for PE estimation. Figure 2 shows the results of the water-year correlations (as a function of the river area in each of the 151 basins) with annual precipitation, the sc-PDSI and the SPEI. The results were very similar among the indices, with no differences as a function of the river area. Thus, the spatial distribution and the magnitude of correlations worldwide were quite similar with respect to the three variables analyzed (Figure 3). Therefore, data aggregation at an annual scale smoothes the hydrological differences that can occur at shorter temporal resolutions (e.g., monthly), which drought indices need to reproduce to be useful for drought monitoring. Therefore, the results presented by D11 do not provide evidence of the better performance of the PDSI for monitoring hydrological droughts on an annual basis.

[20] While drought indices are designed to enable real-time drought monitoring at bi-weekly or monthly time resolutions (e.g., the U.S. Drought Monitor, http://droughtmonitor.unl.edu/monitor.html), strong correlations on an annual basis do not necessarily reflect reliability at these resolutions. This is clearly illustrated by the example of annual streamflow of the Mississippi River (North America), which shows similar strong correlations with annual precipitation, annual sc-PDSI and the 12-month SPEI (0.72, 0.74 and 0.74, respectively). Nevertheless, differences are evident when monthly values are analyzed, and limitations of the PDSI in reproducing hydrological drought conditions become clear. Figure 4 shows the time series of streamflow drought (quantified using the SSI) together with the series of the basin averages of the PDSI and the 4- and 17-month SPEI. The PDSI does not provide a reliable approach to monitoring of the streamflow drought, as it shows temporal variations of higher frequency than the SSI, and the correlation between the sc-PDSI and the SSI is r = 0.57. For this area the sc-PDSI correlates best with the SPEI at a time scale of 17 months (r = 0.85), which is

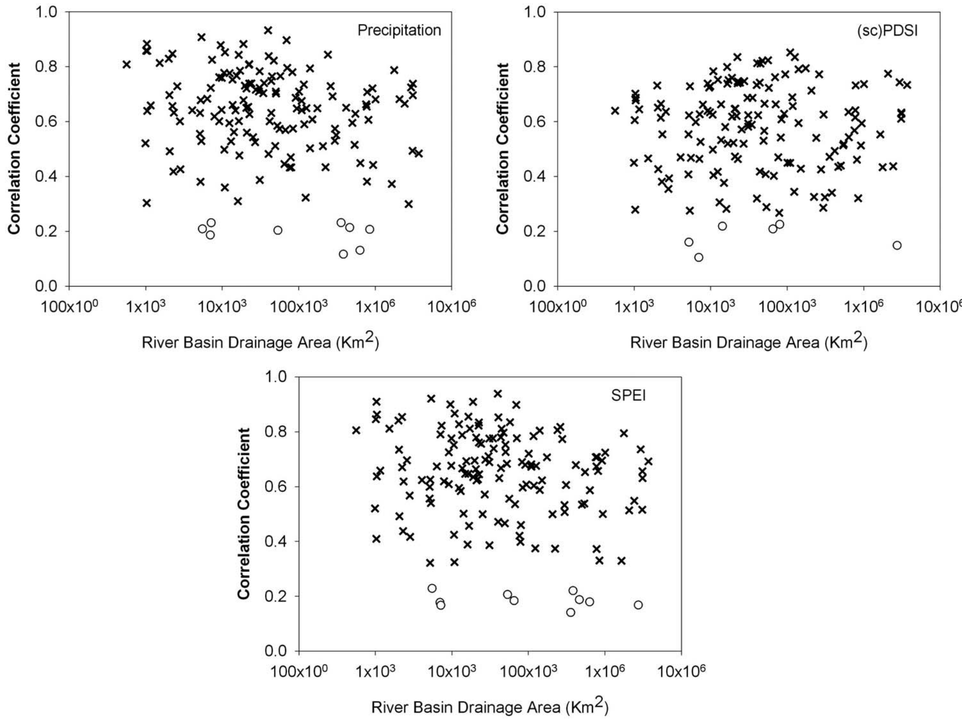

Figure 2. Scatterplot of the correlation coefficient between water-year streamflows in 151 basins worldwide (see Figure 3) and (top left) water-year precipitation, (top right) average sc-PDSI and (bottom) the 12-month SPEI between 1948 and 2004. Crosses indicate statistically significant correlations at the 5% level, while the open circles indicate no significant correlations.

clearly inadequate for monitoring this particular river flow series. In contrast, because of the multitemporal character of the SPEI it is possible to select the most suitable time scale to reproduce the frequency of the target series. In this case the 4-month SPEI has the greatest correlation with the SSI (r = 0.72), enabling reproduction of the observed streamflow of the Mississippi River with reasonable accuracy.

[21] This is also observed in basins that respond to longer time scales. A multiscalar drought index such as the SPEI is adaptable to the specific response time of a particular

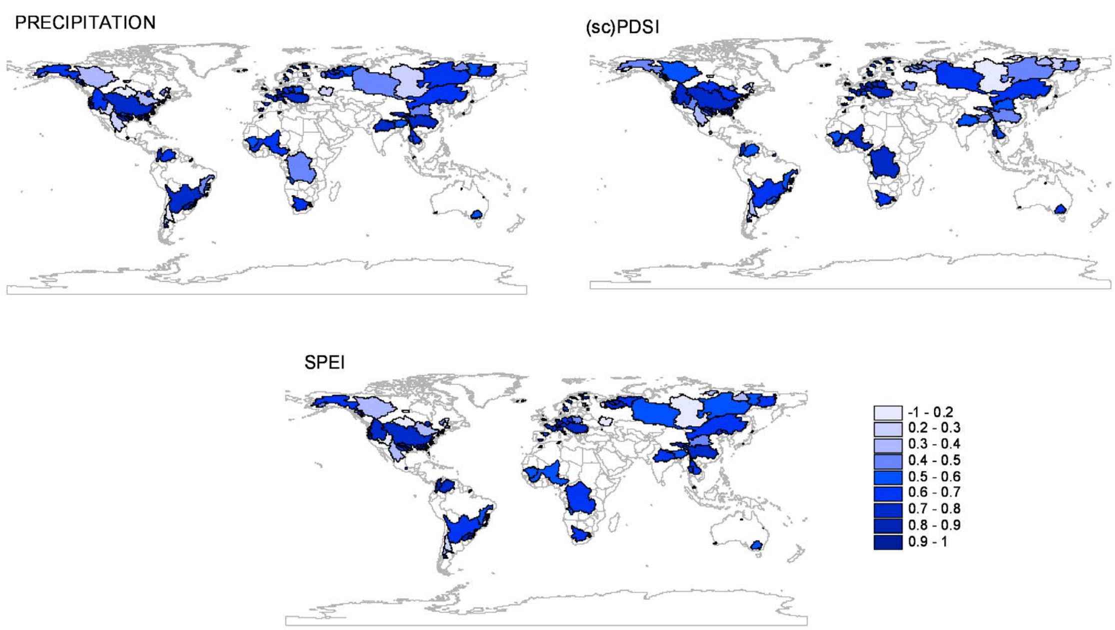

Figure 3. Maps of correlation coefficients between the observed water-year streamflows and (top left) water-year precipitation, (top right) average sc-PDSI and (bottom) the 12-month SPEI in 151 basins worldwide during the period 1948–2004.

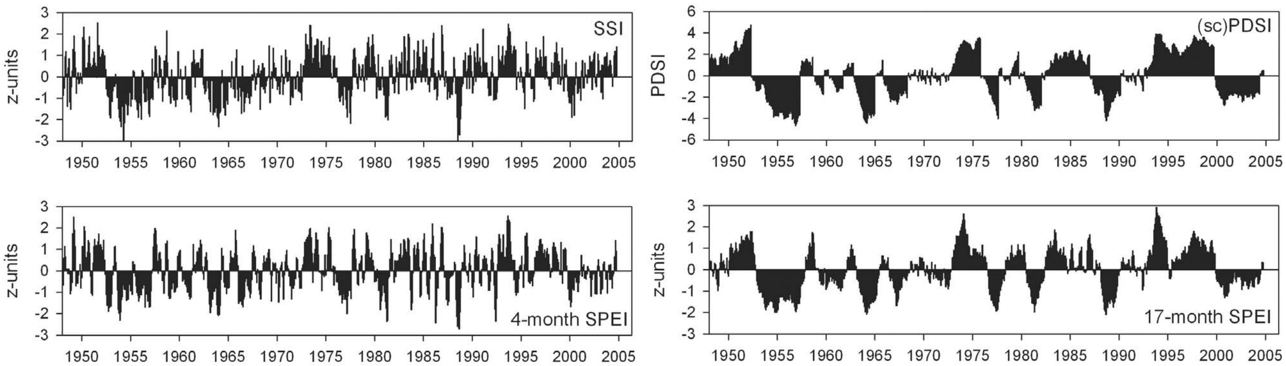

Figure 4. Evolution of the (top left) SSI, (top right) sc-PDSI, and the (bottom left) 4-month and (bottom right) 17-month SPEI in the Mississippi River basin (1948–2004).

catchment. For example, the strongest correlation of the SSI series from the St. Lawrence River between USA and Canada (Figure 5) was with the SPEI at the time scale of 31 months (r = 0.69), while the correlation with the sc-PDSI was weaker (r = 0.59). The strongest correlation between the sc-PDSI and the SPEI was found at the time scale of 14 months (r = 0.85). It could be argued that the PDSI time series can be used as a low-pass filtered to better capture long-term drought effects such as those observed for the St. Lawrence River. However, this would imply double filtering (as the index already has a time scale, or a memory, implicit in its calculation). This makes characterizing the time scale at which the system responds to drought very difficult. However, this is straightforward with use of the SPI or the SPEI, as these indices are conceptually and formally linked to an exact time lag (*m*) used to compute each index. This is not the same as low-pass filtering, as the accumulation is done on the original variable prior to standardization. The SPI and the SPEI maintain units with a robust statistical meaning, and the series of the various time scales are comparable between them. Thus, when making a water balance the PDSI considers the antecedent conditions (a fundamental characteristic of a drought index to determine the duration, magnitude, onset and end of a drought), but multiscalar indices including the SPI and the SPEI also do this. However, these indices have the advantage of determining exactly the period (time scale) in which the antecedent conditions are affecting the value of the index. In addition, the SPI and SPEI are not obtained using smoothing approaches, but by cumulative antecedent climate conditions. Thus, calculation of the time series of a drought index obtained at a given time scale is completely independent of the time series of the index obtained at a different time scale. In addition, the magnitude of the index has a clear statistical meaning, as it is expressed as a standardized anomaly, whereas the units of the PDSI are not so easily interpreted.

[22] An additional problem with smoothing in the PDSI concerns the shortest time scales of drought, which cannot be reproduced by this index. The PDSI represents a fixed time scale that typically varies between 9 and 18 months, with spatial differences among regions depending on local characteristics [*Guttman*, 1998; *Vicente-Serrano et al.*, 2010b]. We agree with D11 that the PDSI was designed to be strongly auto-correlated to account for the impact of land memory on drought conditions, and for this reason it is not able to depict drought on time scales shorter than 12 months. However, time scales ranging from 2 to 9 months are very useful for capturing the drought response in several hydrological, agricultural and environmental systems (such as the SSI of the Mississippi River, described above), and can be used for drought monitoring purposes. Although D11 indicates that other Palmer-related indices, such as the Z-index, can be used

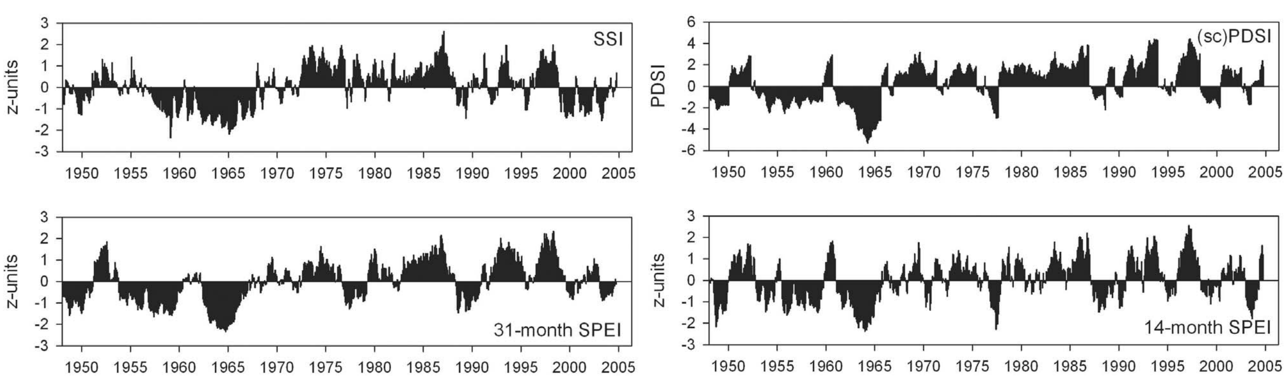

Figure 5. Evolution of the (top left) SSI, (top right) sc-PDSI, and (bottom left) 31-month and (bottom right) 14-month SPEI in the St. Lawrence River basin (1948–2004).

to track short time scale droughts, these share the same problems of the PDSI in that they may not adapt to the optimum time scale at which a system is responding to the drought.

[23] We note that the SPEI and the SPI are not unique measures of drought. Indeed, no drought index is able to fully reflect actual conditions. The best measures of drought are those related to drought impacts in terms of factors such as reduced water resources, economic losses, environmental damage and crop failures. However, climatic drought indices attempt to reproduce drought conditions in a variety of systems, and can be useful for monitoring and early warning. For these purposes the flexibility of multiscalar drought indices is preferable. This is the central basis of our reasoning, and the main *raison d'être* of the SPI and the SPEI.

4. The Problems of Spatial Comparability of the PDSI

[24] The problems of monitoring drought on different time scales are linked to deficiencies in the ability of the PDSI to make spatial comparisons. The problems of spatial comparability in the PDSI were clearly illustrated by *Vicente-Serrano et al.* [2010b], who investigated correlations of the PDSI at a global scale with different time scales of the SPEI. This showed large spatial variability because the PDSI represents water deficits at different time scales depending on the region under consideration. This was initially investigated by *Guttman* [1998], who showed that the spectral characteristics of the PDSI vary from site to site. In other words, the time scales of the PDSI and the sc-PDSI are not fixed because they depend on the characteristics of the sites and vary spatially, making it difficult to assess what kind of deficit the index is representing and making spatial comparisons between sites. This was clearly expressed by *Wells et al.* [2004, p. 2350]: "It is important to note that, while the SC-PDSI is more spatially comparable than either the NCDC or CPC versions, it is not as comparable as an index computed using nonlinear methods (e.g., the Standardized Precipitation Index; *McKee et al.* 1993)." This characteristic of the sc-PDSI does not diminish the considerable effort by Well and collaborators to develop the index, and their considerable advances regarding the PDSI. Nevertheless, in terms of spatial comparability the PDSI retains the problem of being an index that represents different drought frequencies among sites.

5. Conclusions

[25] Several studies have compared the performance of drought indices and their ability to reproduce drought conditions, and these have shown that the SPI is superior to the PDSI [*Guttman*, 1998; *Steinemann*, 2003; *Paulo and Pereira*, 2006]. For example, *Keyantash and Dracup* [2002] tested the efficacy of 18 drought indices and concluded that the SPI was best at quantifying, in spatial and temporal terms, the severity of droughts. Thus, given its substantial advantages in quantifying and monitoring droughts, the SPI has been accepted by the World Meteorological Organization as the reference drought index. In the "Lincoln Declaration on Drought Indices," 54 experts from all regions of the world agreed on the use of a universal meteorological drought index for more effective drought monitoring and climate risk management. They made the significant consensus agreement that the Standardized Precipitation Index (SPI) should be used by national meteorological and hydrological services worldwide to characterize meteorological droughts [*Hayes et al.*, 2011].

[26] Drought scientists are aware of the superiority of multiscalar drought indices including the SPI. With the development of the SPEI we sought to resolve the main criticism of the SPI, namely that it is based on precipitation data alone. The SPI does not consider other variables that can influence droughts, particularly the evapotranspiration demand. Nevertheless, in developing the SPEI we followed the same conceptual approach that McKee and collaborators devised to develop the SPI. *Vicente-Serrano et al.* [2010a] clearly demonstrated that the SPEI has advantages over previous indicators because it combines the sensitivity of the PDSI to changes in evaporation demand (caused by temperature fluctuations and trends), simplicity of calculation, and the multitemporal nature of the SPI.

[27] In summary, we disagree with the criticisms of D11 in relation to drought indices other than the PDSI, and specifically with respect to the SPEI. Our intention in developing the SPEI was not to substitute other drought indices such as the PDSI. As all drought indices are models, access to several is desirable and better than basing studies on a single index. This is clearly illustrated by the U.S. Drought Monitor [*Svoboda et al.*, 2002], which is a system that uses various drought indices and parameters to assess the severity of droughts and their potential impacts. We conclude by stressing that the development and improvement of drought indices is an incomplete task, and numerous challenges remain for the future. Land surface variables including vegetation cover, height and albedo have impacts on water consumption, and consequently on drought severity, but are not incorporated into current drought indices. In addition, with very few exceptions [e.g., *Byun and Wilhite*, 1999] current drought indices do not consider the intensity of precipitation, measured at daily or sub-daily scales, even though intense precipitation (such as convective summer rain) is known to trigger surface runoff, with direct implications for streamflow, soil moisture and the drought condition in general.

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