MS No.: hess-2011-349

Monitoring and quantifying future climate projections of dryness and wetness extremes: SPI bias

Frank Sienz, Oliver Bothe and Klaus Fraedrich

Reply to R. T. Clarke (referee 2)

We thank R. T. Clarke for his encouraging and challenging comments, pointing out problems in a more general sense.

1. Each distribution is an approximation for an unknown truth and observed data is only a part it, a sample. The accepted procedure is, stating a hypothesis and testing its consistency to the data at hand. With respect to the truth it is possible, that a hypothesis found consistent could be false, but this is undecidable. However, an increased sample size or an enlarged observational time period may lead to differing outcomes. In respect to the truth it is possible that, all distributions are wrong and some may be more/less wrong than others. That is, the distribution is of an unknown type or several unknown types. But as noted, this is not decidable on the basis of data alone and a derivation from physical laws is hindered due to the complexity of the involved processes.

The introduced Multi-Distribution SPI (MD-SPI) is one of the discussed alternatives to calculate the SPI. The MD-SPI is motivated by optimised bias variance trade-off, contrary to plausible three parameter distributions (page 10654, line 16). This trade-off is always of relevance for estimation. A more general problem is the dimensionality of monthly precipitation, where dimensions refer to the number of parameters. Here, the presented analysis gives some evidence that a dimension of two is too low to be adequate. The required dimension is at least three to capture most of the complexity of precipitation.

2. Having in mind the problems associated with probability distributions and their estimation, one is tempted to think about alternative ways to calculate the SPI. The empirical cumulative distribution function (ECDF), which is sometimes regarded as the best distribution estimate, is a promising candidate. The ECDF requires no hypothesis about an underlying probability model and the calculation is quite easy. There are, however, difficulties attached to ECDF, which are related mostly due to its its discrete nature, making the ECDF a to coarse measure. The ECDF attributes the same probabilities to the values of time series of equal length and sample sizes from approximately 25 to 65 yield always exactly one extreme dry and one extreme wet SPI event. By contrast, it is likely that there are sites and months where none or more SPI extremes occur, so that the uncertainty can be considered as too high in the lower and upper tails. The discreteness also hamperes SPI monitoring applications and future climate assessments, because reference transforming distributions are needed to extrapolate in both cases. These shortcomings, however, can be avoided or reduced by smoothing the ECDF and applying the smoothed estimate for the tranformation. This combination has the advantage that no distribution assumption is required and the oucome is a continous transformation distribution.

Transforming with ECDF is an interesting alternative and we include parts of the above discussion in Section 4 (page 10654, line 24).

3. Maximum Likelihood estimation and its convergence is critical and a note on that must not miss. At the end of Section 2.2 we include: "The parameters of the distributions are estimated by the Maximum Likelihood method. This is a versatile approach and applicable for all analysed distributions. The maximized likelihood is further the basis for Akaike's information criterion (AIC, Section 2.3). The optimization is performed by a Quasi-Newton-Method and checked for convergence. In the subsequent analysis cases are omitted when convergence is not achieved. The number is below 1% (4%) of all gridpoints and months in the CRU (ECHAM5) data set."

4. A threshold of $0.035 mm/month$ is applied to separate numerical noise present in climate models from "real" precipitation events. An analogy is the lowest observable value given by the measurement device for observed precipitation. Note that, the precipitation values are always higher than $0.1 mm/month$ in the CRU data set. Values below the specified threshold are considered as zero precipitation. For months without precipitation the SPI is calculated according to the procedure introduced by McKee et al. (1993):

$$H(x) = p_0 + (1 - p_0)F(x) \tag{1}$$

Here, the total probability, $H(x)$ used for the transformation consists of the probability for zero precipitation, p_0 and the estimated probability function, $F(x)$. In the given example with 100 years of monthly precipitation and 50 zero values, the probability $H(0) = p_0 = 0.5$ (with $F(0) = 0$) and the resulting SPI value is zero. This is also the lowest achievable value for the given site and month. Consequently extreme dryness is not observable in arid regions. The problem of the SPI lower bound is discussed by Wu et al. (2007).

The above explanations should have been given. We include the motivation for the threshold in Section 2.4 (Page 10643, line 24) and the calculation of the probability in the case of zero precipitation in Section 2.1 (Page 10639, line 19).

5. The linear trends are removed to ensure the stationarity of the precipitation time series for distribution estimation. The subsequent transformation, however, is performed with the original data. In this way the resulting SPI series preserves the trends. The proposed method of time dependent parameters for trend estimation is more adequate than the linear regression used here. But, if the time dependent distributions are used for the transformation the trends are effectively removed in the resulting SPI series. This follows that each of the distributions, at each time step, transformes to the standard normal distribution in analogy to the SPI computations in different climate regimes or seasons. Selecting just one transformation distribution from the time dependent set circumvents this. A comparison between these two possibilities to deal with precipitation trends and their consequences on the SPI needs further analysis. An advantage of the simpler approach taken here is, that the AIC is not influenced by additional parameters in contrast to time dependent distributions.

We explain the applied trend procedure in more detail in Section 2.

6. We agree that climate models have their deficits, especially for precipitation (Section 4, page 10654, lines 7-15), and it is of importance to improve the physical representation of processes and necessary parametrisations. Parametrisations are used mainly to approximate physical processes on small spatial scale, which are not resolved because of too coarse grid resolutions. These parametrisations are constant in time, so that the first and second moments of a variable are affected, but not the time structure, i.e. the autocorrelations. Time dependence results from the buid-in physical processes. The same starting conditions produce the same climate model outcome. This however, does not imply that the statistical properties are incorrect. Computer based random number generators are an example where random numbers can be reproduced by using the same random seed and approaching desired probability properties to a high accuracy. Additionally, the SPI calculation is applied separately for each month. This breaks the month to month dependence and the dependence on a yearly basis can be considered as small. Precipitation in January, for example, yields lag-1 autocorrelations below 0.05 (0.1) in 85% (98%) of all land and ocean gridpoints in the 500 year long ECHAM5 control run (CTL). Maybe of greater importance are dependence structures like clusters in time or instationarities caused by physical processes. Examples are climate modes such as the North-Atlantic Oscillation or El Nino/Southern Oscillation. These affect the statistical analysis of observations and climate models. From our analysis we can not exclude that the distributions are modified or differently preferred with respect to these processes. This might be of interest for future work, where the presented work can serve as a basis.

We will discuss the potential influence of climate modes on the precipitation distributions in Section 4 (page 10654, line 16).

7. The use of statistical methods requires caution in general. This is no unique feature of climate models and holds as well for observational data. It is further essential to apply statistical methods, to the best of our knowledge, to validate and to improve climate models. On the other hand climate models may help to understand observed time series, because of homogeneity, spatial completenes, adjustable sample size and the possibility to carry out numerical experiments, like sensitivity tests.

References

McKee, T. B., Doeskin, N. J., and Kleist, J.: The relationship of drought frequency and duration to time scales, in: 8th Conf. on Applied Climatology, pp. 179–184, American Meteorological Society, Anaheim, Canada, 1993.

Wu, H., Svoboda, M. D., et al.: Appropriate application of the Standardized Precipitation Index in arid locations and dry seasons, Int. J. Climatol., 27, 65–79, 2007.