Comments on "El Niño: Catastrophe or Opportunity"

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In a recent article Goddard and Dilley (2005, hereafter GD05) present a case that the El Niño–Southern Oscillation (ENSO) phenomenon is not related to a greater amount of global socioeconomic losses or climate extremes, expressed in rainfall over land, as compared to non-ENSO (neutral) conditions. Regarding precipitation, Dai et al. (1997) have argued that ENSO is the single largest cause for global extreme events, accounting for 15%–20% of the global variance. This comment specifically addresses whether GD05's use of climate anomalies is an adequate measure of precipitation extremes. Here we present an alternative to the precipitation perturbation index (PPI), and show a substantially stronger relationship between precipitation extremes and El Niño over tropical land areas.

The monthly PPI is constructed by dividing the absolute value of gridded precipitation anomalies by standard deviation and summing over the latitudes 30°N–30°S. This calculation implicitly assumes that the probability density function (PDF) of precipitation follows a normal distribution, which is an incorrect assumption at the monthly time scale. Annual rainfall amounts are approximately normally distributed, but at shorter time scales precipitation PDFs become increasingly skewed toward low values (Hornberger et al. 1998). While precipitation can never be lower than zero, there is a less well defined upper limit. These constraints usually result in distributions with small means and large standard deviations, resulting in the PPI assigning more wet extreme than dry extreme months, as demonstrated below. Legates (1991) used 100 yr of monthly rainfall data from 253 stations covering a wide range of climate regimes to evaluate the performance of eight PDFs. After computing the 12-monthly precipitation distributions on a 50-yr random sample, Legates (1991) then tested the functions on the remaining time series. The normal distribution was ranked last, as 35% of the stations did not meet the 95% significance confidence level for a normal PDF.

For precipitation records longer than 30 yr, as used by GD05, median rainfall is often chosen over the mean as the former better represents central tendency (Wiesner 1970). Furthermore, using specified percentiles of the precipitation PDF guarantees wet and dry extremes, which is not the case if the standard deviation is used.

To demonstrate these ideas, the newly released 50-yr

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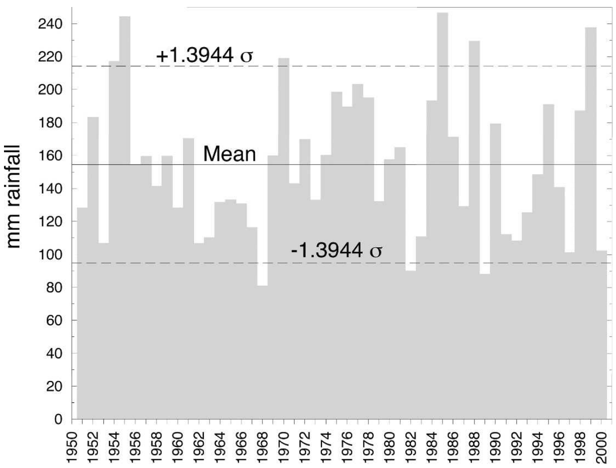

FIG. 1. 1951–2000 October precipitation amounts for the GPCC grid centered at 13.75°N, 61.25°W. Mean and ±1.3944 std dev lines are marked.

precipitation climatology of the Global Precipitation Climatology Centre (GPCC) was analyzed for extreme events. The GPCC dataset interpolates quality controlled observations from about 9500 stations with homogeneous records from 1951 to 2000 at three different resolutions (Beck et al. 2005). In this study 2.5° latitude × 2.5° longitude was chosen.

First, the PPI was calculated with the GPCC dataset as in GD05, but in addition the positive "wet" and negative "dry" precipitation anomalies were summed separately. Second, precipitation for each month of the annual cycle was ranked and percentiles were calculated. A "wet" percentile index was defined as percentiles above 0.5. Percentiles below 0.5 were subtracted from 1.0 to produce an equivalent "dry" percentile index. In parallel with our treatment of the PPI, the summation was carried out separately for the dry and wet indices. Finally, very arid regions were not included in any part of this analysis, namely, locations with a monthly median rainfall of zero.

The PPI and percentile index were in fair agreement when all precipitation values were included in the summation. However, differences emerged when only the tails of the distribution were considered. A Climate Variability and Predictability/World Meteorological Organization (CLIVAR/WMO) workshop on indices and indicators for climate extremes suggested that

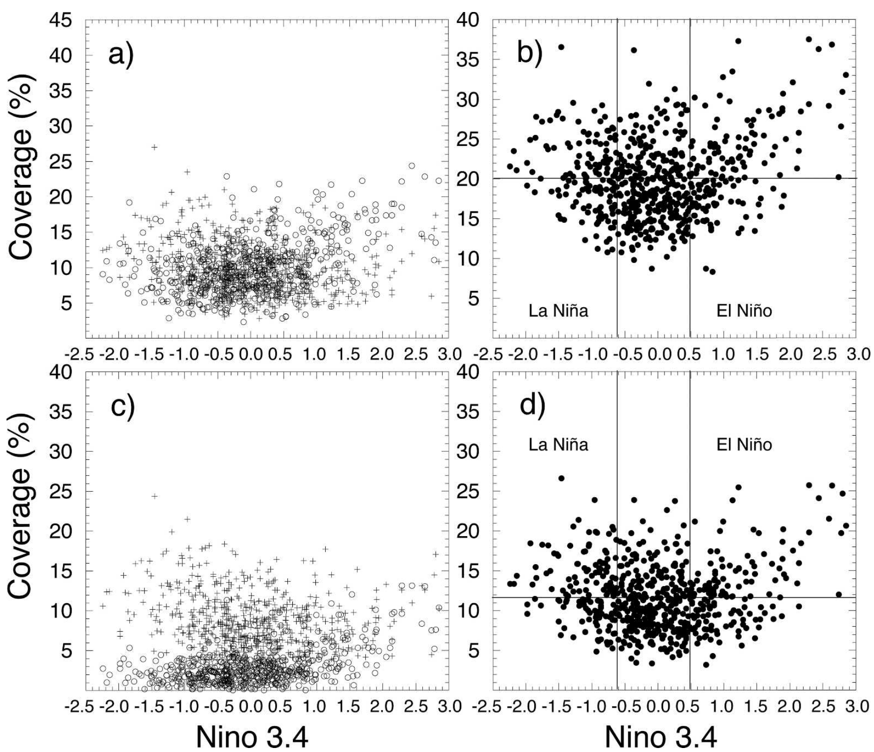

FIG. 2. Percent coverage of extreme monthly precipitation for the GPCC 1951–2000 dataset as a function of ENSO (Niño-3.4): (a) dry (o) and wet (+) extremes as determined by the percentile index, (b) sum of dry and wet extremes as determined by the percentile index, (c) dry (o) and wet (+) extremes as determined by the PPI, and (d) sum of dry and wet extremes as determined by the PPI. For (b) and (d), vertical lines denote the El Niño and La Niña divisions.

when using monthly data serious drought and wet periods be defined as the lowest and highest 10%, respectively, in a year/season (Nicholls and Murray 1999). Thus, monthly extremes were identified by the bottom and top 5 yr of the 50-yr dataset. Assuming normality, these thresholds are equivalent to ±1.3944 standard deviations away from the mean.[1] Hereafter, the analysis of the percentile index and PPI only considers these extreme conditions.

Next we give an example of the differences that arise between the extreme percentiles and standard deviations defined above. Figure 1 shows the October precipitation time series for the humid Lesser Antilles. It is normally distributed according to a Kolmogorov–Smirnov test. The mean rainfall is 154.52 mm and the 1.3944 standard deviation value is 59.73 mm. Although theoretically the numbers should be equal, twice as many years fall outside the +1.3944 standard deviation line than the −1.3944 standard deviation line. In fact, the fourth driest October occurred during the 1997/98 El Niño and would be missed by the PPI.

The fraction of tropical (30°N–30°S) land area covered by extreme dry and wet values are plotted separately and in combination as a function of SST anomalies in the Niño-3.4 region (Fig. 2). The design of the percentile index requires the wet and dry coverage (Fig. 2a) to average 10% (5 out of 50 yr). The PPI (Fig. 2c) has a nearly equal average wet coverage (9.0%) but much lower average dry coverage (2.7%).

Figures 2b and 2d show the combination of dry and wet coverage for the percentile index and PPI. The identification of more dry area by the percentile index during El Niño changes the frequency distribution as seen in Fig. 3. The frequency of El Niño and neutral months is given as a function of ranked spatial coverage in 5% (30 months) increments. El Niño is defined as the upper 25% of Niño-3.4 and neutral as the middle 50%, as in GD05. For the percentile index (Fig. 3a) there is a greater frequency of neutral months as compared to El Niño months when there is a low incidence of extreme precipitation, defined as the first quartile. The opposite is true for a high incidence of extreme precipitation, defined as the fourth quartile. The separation between the El Niño and neutral curves is reduced for the PPI (Fig. 3b). The percentile index also gives a consistently higher frequency of El Niño months in the fourth quartile as compared to the PPI (Fig. 3c). Table 1 encapsulates the coverage differences between the indices for the first (low), second and third (medium), and fourth (high) quartiles. The PPI gives a greater occurrence of extremes for La Niña as compared to the percentile index. However, the largest difference is a 32% increase (28% for PPI; 37% for the percentile index) in the population of extremes during El Niño. This amounts to 13 more El Niño months being classified in the percentile index's high spatial coverage category.

This comment challenges the conclusion of GD05

[1] GD05 use ±1 std dev away from the mean.

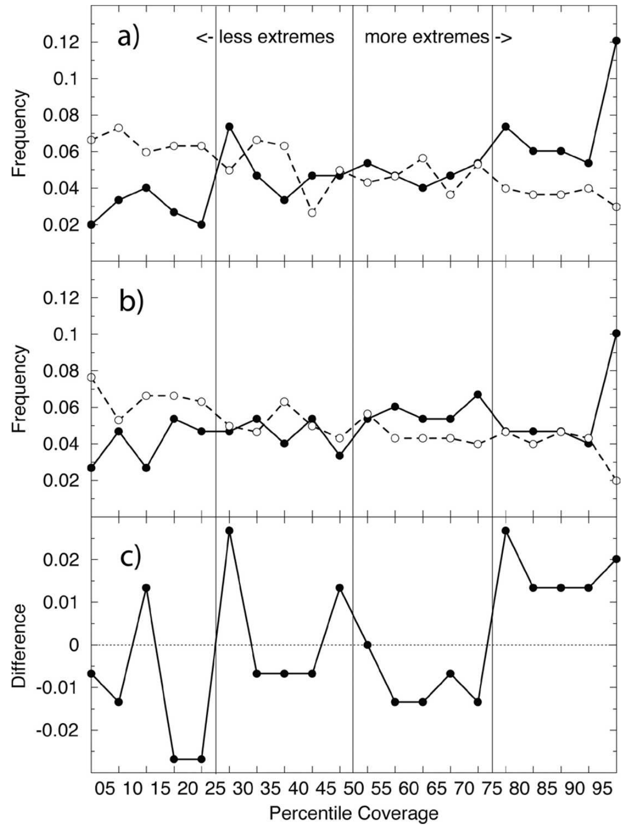

FIG. 3. Frequency distribution of El Niño (solid line) and neutral (dashed line) months as a function of the spatial coverage of precipitation extremes in terms of percentiles. Increasing coverages are to the right of 50 and decreasing coverages are to the left. (a) Percentile index, (b) PPI, and (c) difference between the percentile index El Niño distribution (a) and the PPI El Niño distribution (b).

TABLE 1. Observed frequencies of categorical monthly mean rainfall indices (low: first quartile; medium: second and third quartiles; high: fourth quartile) under El Niño, La Niña, and neutral conditions. The percentile index value is distinguished from the second PPI value in parentheses.

	Spatial coverage of extreme precipitation		
	Low	Medium	High
El Niño	14% (20%)	49% (52%)	37% (28%)
Neutral	33% (33%)	49% (48%)	18% (20%)
La Niña	21% (15%)	53% (53%)	27% (33%)

that "the risk of widespread extreme precipitation anomalies during ENSO extremes is comparable to that during neutral conditions." A percentile index is presented as an alternative to the parametric PPI in representing extreme precipitation on a monthly time scale. The percentile index shows a stronger relationship between the spatial coverage of extreme precipitation over tropical land areas and El Niño. Figure 2a clearly shows that dry extremes account for this relationship. For months when Niño-3.4 exceeded $+1.0°C$ the mean spatial coverage for dry extremes was 14.7% compared to the overall mean of 10%. Furthermore, 86% of the dry coverages were larger than the overall mean. These results have implications for drought prediction, and are consistent with a recent study linking El Niño to global drought in the Tropics (Lyon 2004). Finally, concerning the analysis of climate-related socioeconomic losses in GD05, the authors note that drought disasters occur more frequently in El Niño demise years.

The question posed by GD05, "Do climate anomalies become more severe or widespread during ENSO extremes?" remains open. While the GPCC monthly dataset advances global precipitation analysis, there continues to be undersampling in developing countries, which are at a higher risk for socioeconomic losses. International efforts must be directed at data mining and the maintenance and development of rain gauge sites. Furthermore, while monthly averages are sufficient for describing prolonged dry anomalies, which could equate to drought and socioeconomic losses, intense rainfall is better resolved at the daily (or finer) time scale. Are global daily extremes in precipitation related to ENSO? Because of the paucity of daily rain gauge data, satellites, such as the Tropical Rainfall Measuring Mission (TRMM), may help in addressing this question, but current rainfall algorithms have difficulty with precipitation extremes, and the record is too short for the type of analysis presented here. In conclusion, we encourage further studies to clarify the relationships between hydrometeorological extremes and ENSO.

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