Quantifying Drought – Some Basic Concepts

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Background

Drought differs from other hazard types in several ways. Unlike earthquakes, floods or tsunamis that occur along generally well-defined fault lines, river valleys or coastlines, drought can occur in all climate types with the exception of deserts, where it is ill-defined. Drought typically develops slowly, resulting from a prolonged period (from weeks to years) of precipitation that is below the average, or "expected", value at a particular location. Ultimately, drought represents a condition of insufficient water supply relative to demand, with both being highly location-specific. For example, a few months of deficient rainfall in a particular region may adversely affect rain-fed agriculture but not a reservoir system with substantial storage capacity. And defining what constitutes "deficient" precipitation depends on the local climate.

Drought is often described as falling into three main categories: *meteorological*, *agricultural*, and *hydrologic*. Meteorological drought refers to a usually prolonged period of deficient precipitation. Agricultural drought occurs when soil moisture is depleted to the point where it begins to adversely affect crops, pasture, or rangeland. A reduction in soil moisture is in part related to a lack of precipitation but also depends on other meteorological conditions such as temperature and wind and non-meteorological factors such as soil type and terrain. Hydrologic drought refers to a condition of persistent, below-average surface water levels in rivers, streams, lakes and reservoirs or subsurface water such as an unusually low water table. These conditions are again partially related to precipitation variability but also to non-meteorological factors. Given the importance of non-meteorological factors there is often a delay between the occurrence of meteorological drought and the onset of hydrologic drought, for instance. Because of the different types of drought (related to its varying impacts) and the different time scales over which it operates there is no universally agreed-upon drought definition or method for mapping the drought hazard.

Among natural hazards, drought risk is especially difficult to quantify. Defining what constitutes a drought across the wide range of regional climates around the globe is challenging in its own right, identifying what drought characteristics (intensity, duration, spatial extent) are most relevant to a specific drought-sensitive sector (agriculture, water management, etc.) poses another layer of complexity. To a large extent, drought differs from other hazard types in the way losses are incurred. Drought typically does not destroy infrastructure or directly lead to human mortality. Famines may be triggered by drought but increased human mortality during famine is ultimately linked to a broader set of issues surrounding food security. In addition, the impacts of drought may occur in locations that are largely removed from the drought's occurrence in the meteorological sense. For example, deficient precipitation in the source region of a river system may result in major impacts at downstream locations hundreds of kilometers away. Thus, even once a methodology for defining drought is achieved, evaluating drought risk from drought remains a region-specific challenge. Some examples of the challenge in mapping the spatial distribution of meteorological drought are given below.

Data Issues in Mapping Meteorological Drought

Even when the focus is narrowed to the mapping of meteorological drought, there are several issues to consider. First, not surprisingly, is the quality and representativeness of the meteorological data that goes into the analysis. Station-based precipitation analyses, for example, typically have varying spatial and temporal coverage. Figure 1a, for example, shows the locations of all precipitation stations listed in the Global Historical Climatology Network (GHCN) that is archived at the National Climate Data Center (NCDC). Fig 1b indicates only those stations having at least 90 percent complete data records for the period 1971-2000.

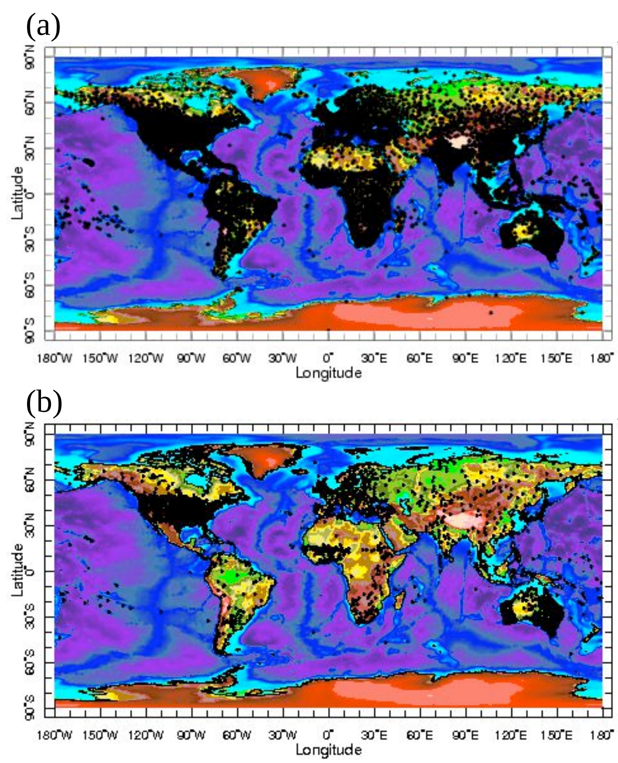

Figure 1. Locations of all stations reporting monthly precipitation as listed in the GHCN data base (a). Locations of only those precipitation stations with at least 90% complete monthly records for the period 1971-2000. Data source is NCDC, data archived at the IRI Data Library at: http://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCDC/.GHCN/.v2beta/

A second example relating to data availability is shown in Figure 2. Plotted in the figure are two time series of the departure from the 30-year average (1979-2004) monthly precipitation based on two versions of the gridded precipitation analyses from the University of East Anglia (UEA). These monthly departures have been averaged across a box that roughly covers the Democratic Republic of the Congo (DRC) and a 12-month moving-average has been applied to both series. Notice the major discrepancies between the series. As was shown in Figure 1, there is comparatively sparse coverage of publically available precipitation data over Africa compared with locations such as the US, Europe and Australia, for example. The gridded UEA precipitation dataset is based solely on station observations so it is clearly going to be impacted by limited station inputs. (It should be noted that the UEA dataset is not limited to only those stations found in the GHCN).

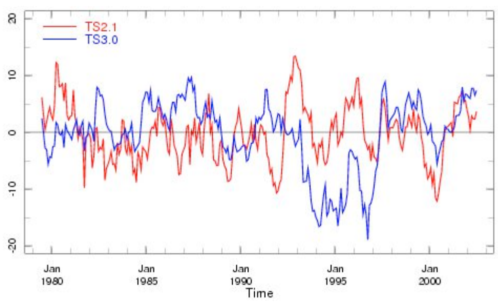

Figure 2. Time series of monthly precipitation departures from the 1979-2004 base period averaged over a region that roughly covers the DRC (10S-6N, 18E-30E). A 12-month moving average has been applied to both time series which are derived from the UEA version TS2.1 and TS3.0 datasets. These are available from the IRI Data Library at: http://iridl.ldeo.columbia.edu/SOURCES/.UEA/.CRU/

Figure 3 indicates how the number of station inputs has varied over time in the UEA data when averaged over the boxed region that roughly covers the DRC. The figure shows the average number of stations within the "influence radius" of a given grid point. Notice that version TS3.0 has many more stations than version TS2.1 over most of the period. Also notice that the number of stations used as inputs has varied substantially over time with the most *recent* period having the fewest number of stations.

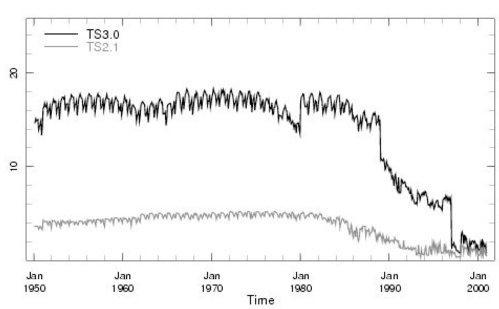

Figure 3. Time series of the average number of stations within the radius of influence of grid points that roughly cover the region of the DRC. Data are from 1950-2000 and are available at: http://iridl.ldeo.columbia.edu/SOURCES/.UEA/.CRU/

Thus, data availability is a major challenge when attempting a global drought mapping study using only publically available data. While the advent of remote sensing from satellites has allowed for more uniform spatial coverage of precipitation estimates, satellites information has only been available for about the past 30 years. And to provide the most utility, such datasets need to be carefully calibrated to observed precipitation.

Drought Index and Base Period Considered

As mentioned, there are numerous drought indicators in use. To be most relevant to specific applications, the temporal fluctuations of such indicators need to be associated with specific impacts. In addition, when attempting to map meteorological drought across locations with differing climatological precipitation a typical approach is to use some form of standardization. This could be done, for example, by looking at precipitation percentiles, percent of median, or an index such as the Standardized Precipitation Index (SPI). The SPI is in wide use around the world and what is essentially done is to first fit a cumulative distribution of observed precipitation over a given time period (typically 1 month to multiple months) and then map the associated probabilities onto a unit normal distribution N(0,1) as shown in Figure 4. The advantage in doing so is that the value of the index in one location can be directly compared with that of a different region. The disadvantage is that, by definition, drought (usually associated with values of less than -1.0) will occur with essentially the same overall frequency at all locations.

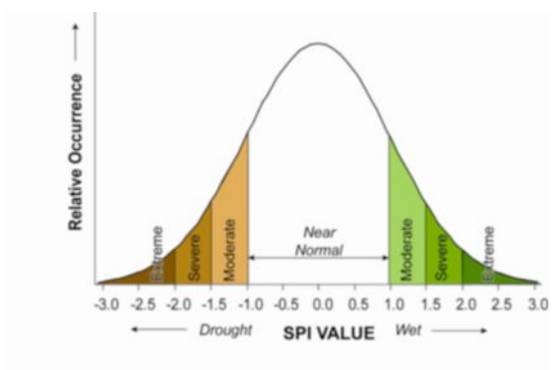

Figure 4. Distribution of the SPI. Average conditions have a value of 0 with increasingly dry conditions given by negative values of the index. By design, the overall frequency of occurrence of the SPI is essentially the same at all locations.

In addition, as mentioned the SPI (and other indicators) can be evaluated over different time periods (e.g., 3 months, 12 months, etc.). Which time period is best to use? That depends on what aspect of drought and associated impacts are being considered (and again, how the index corresponds to those impacts). Even for the same sector, say agriculture, the impacts of drought on crops in the semi-arid tropics with a short rainy season are likely to be different than the impacts on crops in temperate climates in a location with precipitation throughout the year.

Figure 5 shows two time series for the 3- and 12-month SPI for the lower Hudson Valley based on data from NCDC. Notice there are times when one indicator indicates wetter than average conditions while the other indicators reveals drought. For example, during the period starting around 2005 to the end of the time series, the 12-month SPI barely drops below zero, while the 3-month SPI is substantially negative several times. The linear temporal correlation between the 3- and 12-month SPI time series over the full time period 1950-2010 is 0.6. Thus, less than 40% of the variance of one time series is explained, in this linear sense, by the other.

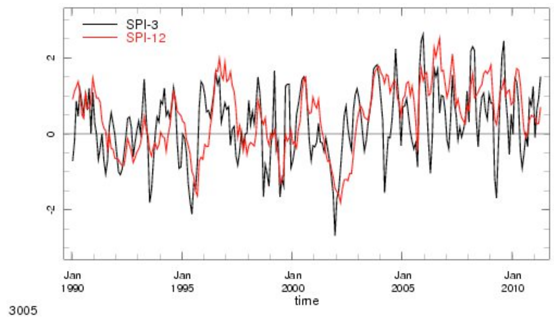

Figure 5. Time series of SPI-3 and SPI-12 for the lower Hudson Valley for the period January 1990 – April 2011 (base period used is from 1950-2011. The precipitation data used to generate the SPI time series originates from NCDC and is available from the IRI Data Library at: http://iridl.ldeo.columbia.edu/expert/SOURCES/.NOAA/.NCDC/.CIRS/.ClimateDivision/.pcp/

As a final example, the base period considered when mapping drought frequency is very important. There are well-known decadal (i.e., slowly evolving) variations to the climate system that result in drought being more frequent during some decades compared with others. A classical example is the Sahel, which during the 1950's and 60's was relatively wet while the 1970's and 80's brought much more widespread and severe droughts to the region. An example of this from the US is provided in Figure 6, which shows time series plots of the 12-month SPI computed for precipitation averaged across the southern Plains (90W-115W, 29N-42N). The base period used to compute the SPI was from 1931-2000, with two, thirty-year sub-periods plotted. The precipitation data used was from the UEA dataset. The dashed lines in Figure 6 indicate a threshold of -1.5 for the SPI, indicative of drought. The total number of years in which the SPI was less than -1.5 during the period 1931-1960 was 8; for 1971-2000 it was 2. A simple approximation to the return period of drought is given by

$$T = \frac{1}{1-p}$$

where T is the return period (in years) and 1- p is the probability of exceedance in any given year. In the above case both periods cover 30 years so 1-p is equal to 8/30 during 1931-1960 and 2/30 during 1971-2000. The corresponding return periods are 3.75 years and 15 years, respectively. Major droughts occurred in the southern Plains during the 1930s and 1950s, so if this period is excluded from the analysis, the overall estimate of drought return period is biased towards the higher value.

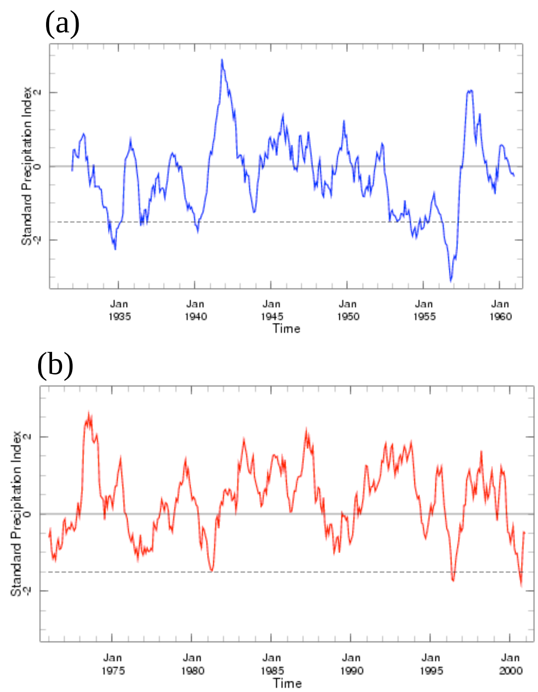

Figure 6. Time series of SPI-12 for the southern US Plains for the period (a) 1931-1960 and (b) 1971-2000. The base period used to compute the SPI was 1931-2000, with the computation based on UEA data (http://iridl.ldeo.columbia.edu/SOURCES/.UEA/.CRU/.TS2p1/.monthly/.prcp/).

Summary

Overall, the unique characteristics of drought make it difficult to analyze vulnerability and risk in the same framework as the other hazard types. Available loss data sets do not provide information on the factors contributing indirectly to drought mortality, while mortality itself is not a good indicator of impact. Similarly, there is also no clear way to translate meteorological drought into agricultural drought since it depends on the farming system and even on individual crop choice. Specific risk and vulnerability to droughts and how they affect income, consumption, health, human development and productivity are therefore best analyzed in detailed local and context specific studies.

Despite these challenges, in contrast to other natural hazards drought is a slow onset phenomenon making it particularly amenable to the development of early warning systems. In addition to its slow onset, a major climate factor leading to drought, particularly in tropical locations, is the El Niño-Southern Oscillation (ENSO) phenomenon. Advances in climate science have made possible skillful seasonal predictions of both ENSO and its associated seasonal rainfall variations with three or more month lead-time. Thus, the combination of real time drought monitoring and availability of seasonal rainfall forecasts constitutes a solid foundation for a drought early warning system.

This summary is based on the NGI report, Natural- and Conflict-Related Hazards in the Asia-Pacific, 15 March 2009.