Chapter 11
Indices for Meteorological and Hydrological Drought

John Keyantash

11.1 Overview

Drought is a deceptively difficult phenomenon to quantify. Drought is most basically defined as a deficiency in water supply, which is occurring with an uncommon frequency and/or severity. It is a natural disaster that is plainly comprehended by farmers, fishermen and the general public, but this simplicity belies the variety of forms in which drought may manifest itself. First, there is the issue of which natural reservoir is deficient in water: surface water, groundwater and/or the root water zone? Due to the interconnectedness of the hydrological cycle, a water shortage in one reservoir (e.g. soil growing zone) is usually mirrored by a deficiency in another (e.g. surface runoff), although the shortages may be time-lagged. For example, groundwater droughts typically lag surface water droughts by several months to years. Nonetheless, delineating the principally affected reservoir is a common approach to simplify drought description. This isolationist approach has led to the recognition of several drought forms.

11.1.1 Drought Forms

There are four primary forms of drought. A shortage of precipitation is known as *meteorological* drought, while a shortage of soil moisture is termed *agricultural* drought. A decrease in surface water (streams, lakes and/or impounded reservoirs) or groundwater levels is known as *hydrological* drought. Finally, *socio-economic*

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A. Pandey et al. (eds.), *Hydrological Aspects of Climate Change*,
Springer Transactions in Civil and Environmental Engineering,
https://doi.org/10.1007/978-981-16-0394-5_11

drought is the consequence of multiple water deficiencies upon society. It is measured not only in terms of various water supplies, but also in terms of monetary cost to the economy.

11.1.2 The Metric for Deficiency

Aside from associating the water deficiency with a specific natural reservoir—and therefore a form of drought—another rudimentary consideration is how to quantify the shortage. For example, a hydrological drought could result in the reduced water supply within an unconfined aquifer. How might the groundwater deficiency be best described? There is no universal answer: metres of water table decline, megatons of absent water or the per cent change in the storativity of the aquifer are all valid metrics. Furthermore, once a direct measure is adopted, how does its value reflect the statistical unusualness of the situation? The desire to interpret the water deficiency in terms of its probability of occurrence is a fundamental property of drought studies. As we will see, this probabilistic component is at the heart of some of the most widely used drought indices.

11.1.3 Timescale Considerations

The statistical analysis of probabilities inevitably involves the consideration of time: over which time frame is the water deficiency occurring? For example, over months or decades? The timescale is commonly considered with respect to the typical expected dryness for the location, that is, the local climate. For example, a meteorological drought in India's Western Ghats would be entirely different than drought in Algeria, in terms of the length of the dryness interval (e.g. months versus years, respectively) and the absolute water deficiency: metres in India to scant millimetres in North Africa.

11.1.4 The Drought Index Approach

For these complicated reasons, the scientific community commonly uses indices to describe drought, rather than direct observations of the water quantity (which are easy to comprehend but do not provide a broader context for the deficiency). But just like there is no single form of drought, there is no single drought index which works best in all circumstances. Instead, various drought indices have been developed which target each physical form of drought: agricultural, meteorological and hydrological (as well as some composite versions). Highlights for a broad suite of indices may be found in WMO and GWP (2016), while Keyantash and Dracup (2002) and Heim (2000) expand upon selected drought indices in more depth.

It bears mention that socio-economic drought does not have a distinct index to describe it, other than financial damages (for example, dollars or rupees). Due to this abstraction from the physical world, socio-economic drought will not be discussed further, and agricultural drought will also be omitted, as this chapter is primarily concerned with the meteorological and hydrological forms of drought.

11.2 Meteorological Drought Indices

This section discusses four indices of meteorological drought: Palmer drought severity index, rainfall deciles, standardized precipitation index and the related standardized precipitation evapotranspiration index.

11.2.1 Palmer Drought Severity Index (PDSI)

In 1965, Wayne C. Palmer published a U.S. Weather Bureau report titled *Meteorological Drought*, in which he outlined the methodology for the calculation of what came to be known as the Palmer drought severity index (PDSI). In subsequent decades, the PDSI went on to become the most widely used index of meteorological drought in the USA. The enthusiasm for this index was related to its attempt, as Palmer put it, of "measuring the cumulative departure of moisture supply" (Palmer 1965). The integrative nature of this approach is at the heart of all drought studies. The PDSI is a dimensionless number typically ranging between 4 and −4, with negative quantities indicating a shortage of water. Near-normal conditions are ± 0.5, while drought occurs when the PDSI is <-1.

The PDSI incorporates a two-layer soil model and calculates water balance within the soil, depending upon observed meteorological conditions. The fluctuations in the hypothetical moisture supply are compared to a reference set of water balance terms. This comparison leads to computation of the dimensionless PDSI. Index values are calculated on an ongoing basis by the US National Centers for Environmental Information (NCEI) (formerly known as the National Climatic Data Center [NCDC]), and monthly PDSI values extend back to 1900 (NCEI 2020). Computation of the PDSI is complicated; for an in-depth discussion of the numerical steps, see Alley (1984).

The PDSI was intended to be a standardizing measure of moisture conditions across different geographic regions and time. However, it was empirically calibrated using various soil types in the Midwestern United States, which are not necessarily representative of other regions. Guttman et al. (1992) determined that routine climatological conditions tend to yield more severe PDSI measures in the Great Plains of the USA than other regions. Thus, there exist regional biases.

The PDSI is also imprecise in its water balance accounting. The two-layer soil model is constructed such that no water may migrate to the underlying layer until the surface layer is at its full water holding capacity, set at the arbitrary level of 25 mm (Alley 1984). There is also no consideration for the delayed hydrological availability of snowfall, which is instead treated as immediately available liquid water. On the positive side, the PDSI does factor in antecedent conditions and is calculable from basic observational data. But its empirical nature, coupled with the fact it was developed for US agricultural regions, limits its broad applicability, and as a result the PDSI is not widely used internationally.

11.2.2 Rainfall Deciles

Precipitation distributions are decidedly non-normal, featuring asymmetry with positive skewness. For example, a comprehensive study of precipitation time series in the USA found that the Pearson type-III and kappa distributions best describe precipitation records for hundreds of sites, although the two-parameter gamma distribution has been widely used to characterize precipitation probabilities (Ye et al. 2018). Since the mean does not lie in the centre of an asymmetric (probability distribution) function, meteorological drought assessments involving variations from the mean precipitation are not equally comparable in their positive (wet) and negative (dry) phases. These imbalances can be circumvented by judging precipitation totals with respect to the median rather than the mean. Such an approach utilizes precipitation quantiles as proxies for direct precipitation measurements.

An established quantile methodology is the usage of ten quantiles, or *deciles*. A decile-based system for monitoring meteorological drought in Australia was proposed by Gibbs and Maher (1967), and adopted by the Australian Bureau of Meteorology (BOM) to monitor drought conditions in that nation. The BOM-adopted characterizations of decile levels are shown in Table 11.1 (Kinninmonth et al. 2000).

Despite having five categories, this is indeed a decile rather than a quintile system, as the bin width of each characterization is not constant. It should also be noted that "average" in Table 11.1 actually implies the median (50th percentile) rather than the arithmetic mean, as a fundamental purpose of the quantile approach is to avoid

Table 11.1 Characterization of rainfall deciles

Decile(s)	Characterization
1	Very much below average
2–3	Below average
4–7	Average
8–9	Above average
10	Very much above average

the distorted values of the mean, which results from Australia's erratic precipitation climatology.

The rainfall decile methodology begins by assembling three-month (or longer) precipitation totals, which are ranked against climatological records. If the precipitation sum falls within the lowest decile (tenth percentile or lower) of the historical distribution of totals sharing that timing (i.e. those particular months of the year) and duration (viz. 3 months or longer [as drought is not validly recognized for briefer periods in Australia]), then the location is considered to be experiencing a "rainfall deficiency" (drought). The first-decile totals are parsed into two characterizations: *serious* (drought) if the precipitation total is between the 10th and 5th percentiles and *severe* if it is below the 5th percentile (Kinninmonth et al. 2000). A decile map of 12-month precipitation totals is shown in Fig. 11.1.

It is interesting that BOM also examines monthly rainfall totals from the decile perspective, even when drought characterization is not the objective; see Fig. 11.2. Thus, deciles are a useful probabilistic lens with which to view precipitation, particularly within a region of naturally high climatic variability, such as Australia.

The *severe* or *serious* forms of meteorological drought are considered to persist until either of two termination criteria occur (Kinninmonth et al. 2000). These termination criteria can be thought of as forward-looking or backward-looking triggers, which are practically employed using a three-month window of inspection:

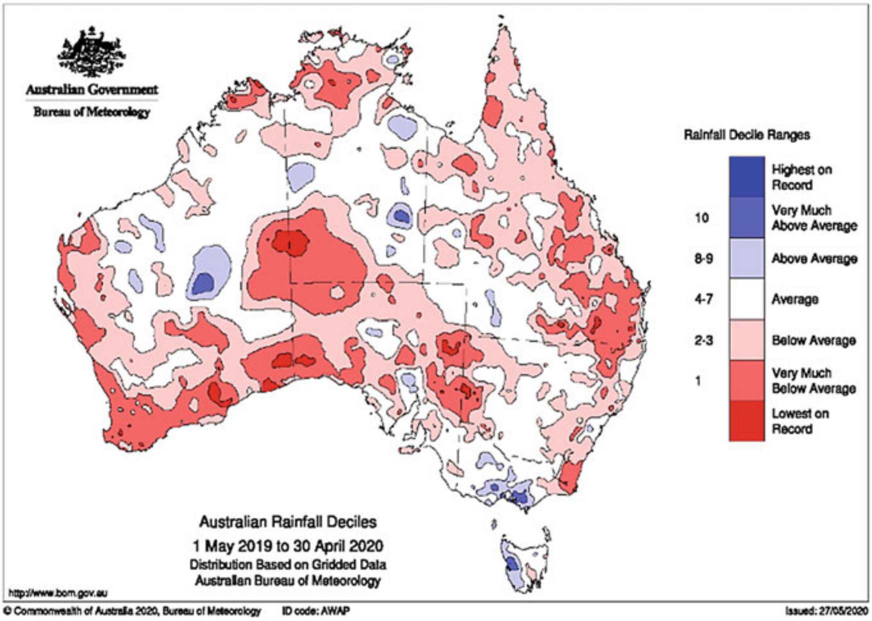

Fig. 11.1 Decile map of 12-month precipitation totals in Australia, through April 2020. Meteorological drought in Australia may be assessed across a variety of timescales, but the duration must be a minimum of three months. *Source* BOM 2020

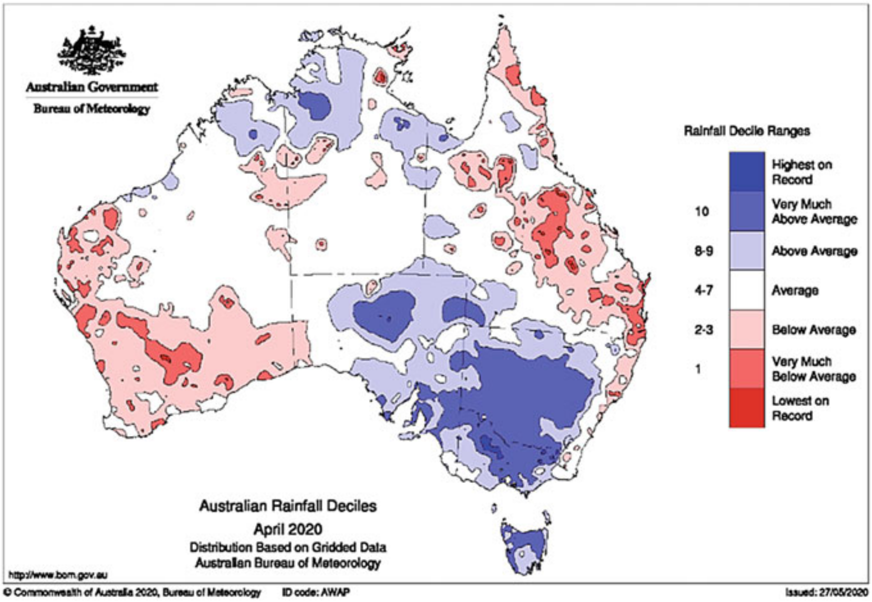

Fig. 11.2 Monthly precipitation deciles across Australia. Red regions are not necessarily experiencing drought (for drought identification, refer to Fig. 11.1), but the decile perspective is useful for judging precipitation deficiencies. *Source* BOM 2020

1. Forward-looking: The precipitation measured during the past month already places the new, forward-looking three-month total in the 4th decile or higher. That is, the three-month total will be "average" (median) or higher (per Table 11.1), even if no further precipitation falls in the next two months. The drought is therefore broken by an unusually wet month. (*But see following* **Rule restriction** *sect.*)
2. Backward-looking: The precipitation total for the past three months is in the 8th decile or higher. Thus, to exit a sustained drought, the three-month rainfall must be above or very much above average.

Rule restriction

In regions with highly seasonal precipitation, it is mathematically possible for a slight amount of precipitation at the start of a typical dry season to trigger the forward-looking drought-stopping condition. In this case, a further rule restriction is applied: the drought does not terminate unless the total precipitation for all months since the drought began exceeds the first decile (G. S. Beard 2000, personal communication).

For example, consider a hypothetical ongoing drought in its eleventh month. The eleventh month of the drought occurs during the start of the typical dry season, and it happens to be a relatively wet month. On its own merits, the eleventh month precipitation would result in the forward-looking precipitation total (i.e. months 11–13) being in the fourth (or higher) decile, which would activate the forward-looking trigger to indicate that the meteorological drought—*serious* or *severe*—had ended. However, before declaring the drought over, BOM would inspect the eleven months since the start of the drought to verify that the 11-month precipitation total was in the second (or higher) decile. In all cases, the termination criteria require the precipitation quantities to exit the lowest deciles and shift to higher deciles.

11.2.3 Standardized Precipitation Index (SPI)

Despite the nonparametric simplicity and utility of rainfall deciles, the scientific world values parametric distributions, as they provide the ability to extrapolate the probabilities of events beyond the observational record. In particular, the widespread usage of normal (Gaussian) statistics motivates data transformations which can re-express skewed, unimodal precipitation data into normal distributions.

The data transformations may involve raising the original data to various exponential powers within specific mathematical functions, with the form of each function depending upon the sign of the exponent. This approach is referred to as a *power transformation*, as an exponential power is involved in performing the transformation. The Box–Cox transformation (Box and Cox 1964) is a classic approach which involves scaling the original data and exponentiating it to the *transformation parameter* λ (lambda). A simpler variant is given by Wilks (1995):

$$T(P) = \begin{cases} P^{\lambda} & \lambda > 0 \\ \ln(P) & \lambda = 0 \\ -P^{\lambda} & \lambda < 0 \end{cases} \tag{11.1}$$

where

P = observed precipitation
T = transformed precipitation
λ = transformation parameter

Obviously, the choice of λ will fully dictate the resulting distribution of the transformed data T. Positively skewed data (i.e. data with a pronounced right tail, such as precipitation) will shift leftwards towards normality when $\lambda < 1$, while negatively skewed data redistributes rightwards when $\lambda > 1$ (Wilks 1995). The precise choice for the value of the transformation parameter that produces the optimal transformation requires some data exploration, and guidance is given in other references (e.g. Box and Cox 1964; Wilks 1995).

In 1993, McKee et al. proposed the standardized precipitation index (SPI) as a way to measure the intensity of drought—in a probabilistic perspective—across multiple timescales. The SPI is anchored upon defined probabilities for each SPI value, in particular the probabilities associated with a Gaussian (normal) distribution of SPI values. Precipitation is not normally distributed, but as discussed in the previous paragraph, it may be transformed to a normal distribution. McKee et al. (1993) considered precipitation data to follow the gamma (Γ) distribution and performed the appropriate transformation. The gamma distribution is one of several recognized extreme value distributions for precipitation (such as Gumbel, Pearson type-III and generalized extreme value [GEV] distributions, among others; refer to Ye et al. (2018) and Guttman (1999) for more thorough discussion), and it benefits from wide acceptance in hydrology and related fields.

The SPI is the standardized precipitation anomaly, *after* the precipitation data have been transformed from their original distribution (nominally gamma) to the normal distribution:

$$SPI = \frac{P - \bar{P}}{\sigma_P} \tag{11.2}$$

where

P = precipitation datum
$\bar{P}$ = mean precipitation
σ_P = sample standard deviation of precipitation

Effectively, the SPI is the expression of the normalized precipitation data as Gaussian variates. Each SPI value has an associated probability of occurrence, given by the routine Gaussian cumulative distribution function, shown in Fig. 11.3. For example, Fig. 11.3 shows that an SPI value of −1 or lower occurs approximately 15% (9% + 4% + 2%) of the time (absent rounding approximations, the actual probability is 15.87%). Per the given SPI categories, these would comprise the "dry", "moderately dry" and "extremely dry" sub-classifications of drought. As shown on the right

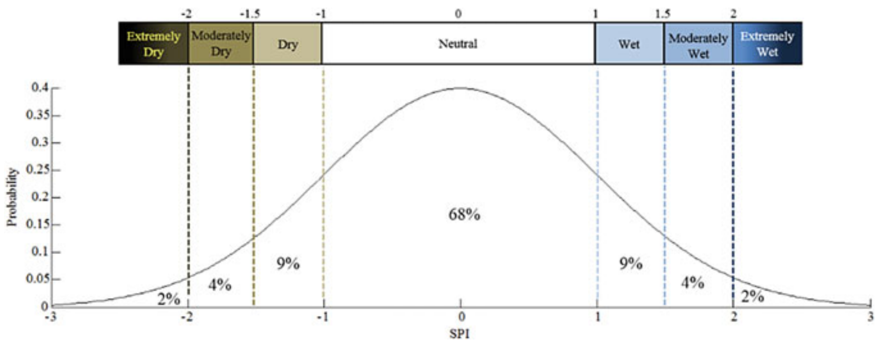

Fig. 11.3 Normal curve and its associated probabilities. The given probabilities represent the likelihood of falling strictly within the dashed boundaries. The sum of the probabilities is less than 100% due to rounding. The colour bar along the top indicates the associated drought labels for the SPI. *Source* Keyantash and NCAR 2018

side of Fig. 11.3, we also see that the SPI is equally suited to represent wet spells (*pluvials*).

A critical benefit of the SPI is that it can be used to characterize droughts across multiple timescales. Specifically, the P value in Eq. 11.2 may be the precipitation total from any particular timescale: one month, three months, 18 months, 72 months or any other desired interval. This grants the SPI the ability to assess dryness across a sliding range of perspectives. For example, a recent wet month might be embedded within a seasonal moderate drought, which in turn is a portion of a multi-year severe drought. The basic question, *"Are we in a drought, and if so, how severe is it?"* produces a complex answer, dependent upon the timescale of interest. The SPI is able to provide quantitative responses across multiple timescales.

The probabilistic foundation for the SPI, coupled with its multi-scale flexibility, has led to its international acceptance. In 2009, at a conference hosted at the University of Nebraska-Lincoln, an international panel of drought experts decreed that among the variety of available meteorological drought indices, the SPI was recommended as the international standard. This statement was known as the Lincoln Declaration on Drought Indices and is detailed more fully by Hayes et al. (2011).

11.2.4 Standardized Precipitation Evapotranspiration Index (SPEI)

A related variant of the SPI is the standardized precipitation evapotranspiration index (SPEI [Vicente-Serrano et al. 2010]), which includes temperature in its computation. The purpose of this inclusion is to recognize that the true deficiency of water depends upon evaporative demand—a reduced water input is less deleterious in a cool climate than a region which is warm and arid. For example, 5 cm of precipitation could produce strong or weak drought relief, depending upon not only the precipitation climatology, but also the evaporative conditions. For the SPEI, monthly mean temperature is used to compute potential evapotranspiration via a Thornthwaite model, and it is the difference of the precipitation and potential evapotranspiration which undergoes transformation to a normal distribution, using a log-logistic distribution (Vicente-Serrano et al. 2010). But once the SPEI is computed, the interpretation of the index follows the same track as the SPI; the inclusion of temperature data results in a different index value (and probability) than the SPI, but the same underlying merits guide the interpretation of SPEI and SPI values alike: direct probabilities across multiple timescales.

11.3 Hydrological Drought Indices

Hydrological drought indices look at water supply conditions, with *water supply* being represented by surface water and groundwater. Due to the transport and storage aspects between surface water and groundwater, hydrological drought indices represent drought over longer timescales than meteorological drought indices. The hydrological drought indices discussed here are the total water deficit and the surface water supply index.

11.3.1 Total Water Deficit

Total water deficit is a straightforward concept. During the course of prolonged drought, there is an accumulated shortage of water. In *meteorological* drought studies, this would be known as the *cumulative precipitation anomaly* and would be the sum of monthly or annual precipitation deficiencies (where each anomaly is the difference between the observed value and its mean). For *hydrological* drought studies, the cumulative anomaly is termed the *total water deficit*. It is the cumulative volume of water which is deficient over the examination period, expressed plainly in units of volume.

The total water deficit may be represented graphically. Figure 11.4 shows a time series depiction of the total water deficit, in which the water supply fluctuates over time. The cumulative deficiency—the drought severity S—is represented by the total

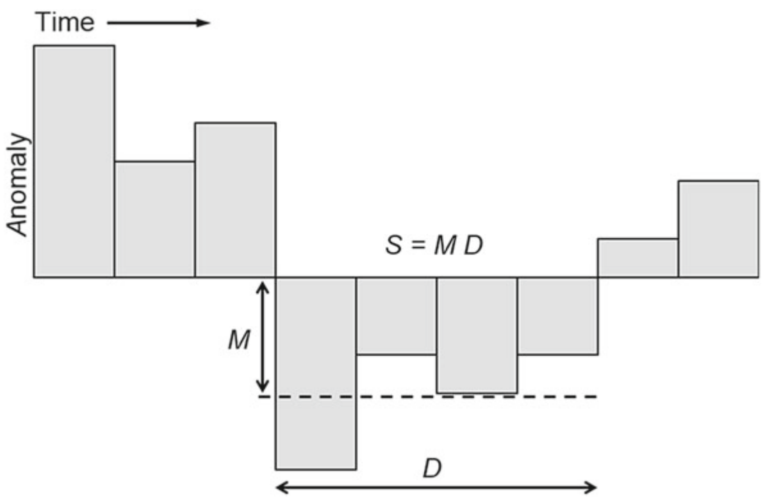

Fig. 11.4 Drought severity represented as the product of drought duration and its average magnitude. When the severity represents a volume of surface or groundwater, the severity is known as the *total water deficit*. Modified from Keyantash and Dracup 2002

barred area beneath the horizontal axis (which is set at the hydroclimatic mean). The water-deficient portion of the time series has a duration D and an average drought magnitude M (Dracup et al. 1980). It should be noted that drought severity, duration and magnitude alternatively appear in the research literature as the run sum, run length and the run intensity,[1] respectively (e.g. Yevjevich 1967). These are fully synonymous terms.

For surface water bodies, such as lakes or reservoirs, the total water deficit is determined by summing the storage anomalies (which may have positive or negative sign). Each anomaly, in turn, is computed by knowing the depth of the reservoir and referencing a depth–volume (or *hypsographic*) curve for the water body. The mean storage is subtracted to reveal each anomaly:

$$V'(t) = V(y(t)) - \bar{V} \tag{11.3}$$

where

V = volume (e.g. km^3 or hm^3)
t = time
y = depth
$\bar{V}$ = mean reservoir volume

Primed quantity is the anomaly.

The total water deficit is the sum of the anomalies during the n months (or years) of the hydrological drought:

$$\text{Total water deficit} = \sum_{t=1}^{n} V'(t) \tag{11.4}$$

The concept of total water deficit also applies to a flowing surface water body, such as a river. However, instead of volume, the principal variable is the discharge Q, possessing units of volume per time (e.g. cubic metres per second). Each discharge value requires multiplication by a time conversion factor T—which relates the denominator of the discharge to the duration of each t—to produce the familiar volumetric units of the total water deficit. For example, if annual mean discharge were expressed in cubic metres per second, and we were tracking a water deficit over n years, $T = 31{,}536{,}000$ s per year. For annually averaged discharge data,

$$\text{Total water deficit} = \sum_{t=1}^{n} V'(t) = \sum_{t=1}^{n} Q'(t) \cdot T$$

[1] Take special note to not inadvertently exchange the words *intensity* and *severity*, as they are distinct terms. Intensity implies the average strength, while severity indicates the cumulative effect. To wit, PDSI does not stand for the Palmer drought *intensity* index.

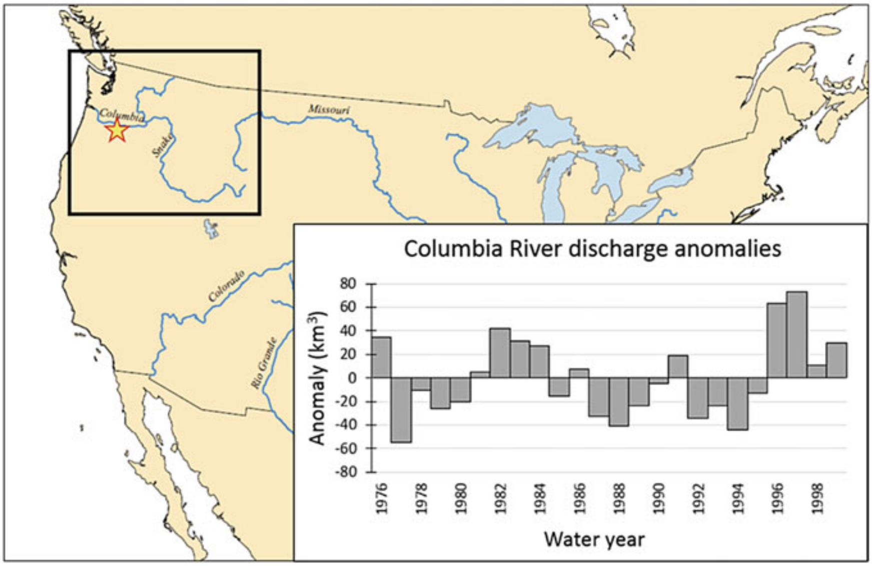

Fig. 11.5 Annual discharge anomalies for the Columbia River, 1976–1999. Modified from Keyantash and Dracup 2002

$$= T \sum_{t=1}^{n} \left[Q(t) - \bar{Q} \right] = T \sum_{t=1}^{n} Q(t) - T n \bar{Q} \tag{11.5}$$

Equation 11.5 is suitable for annual data only. For monthly (or even daily) data, modifications must be made to the summation indices in Eq. 11.5, as the monthly/daily means vary from one datum to the next (i.e. $\bar{Q}$ is not constant across all t).

An example of the total water deficit is given for the Columbia River, a major waterway in the northwest portion of the USA, shown in Fig. 11.5.

At the starred measurement location in Fig. 11.5, the Columbia River has a mean discharge of 5150 m^3/s or 163 km^3 per year. The river experienced three prolonged hydrological droughts during the 24-year period from 1976 to 1999. Each drought had a duration of four years, and all were comparable in terms of severity: the first drought had a total water deficit of 112 km^3, the second had a water deficit of 102 km^3, and the third was the most severe, at 115 km^3. The third drought had a magnitude of 28.8 km^3/yr, and over the four-year duration its total water deficit represented 71% of the mean annual discharge. Thus, the effect of the 1992–1995 hydrological drought was as if the perennial Columbia River stopped flowing for over eight months.

11.3.2 Surface Water Supply Index (SWSI)

Much of the environment in the Western United States is mountainous and/or arid, including a large number of locations subject to rain shadow effects. There is also a seasonal precipitation regime, and the mountains receive a large fraction of their annual precipitation as snowfall, which is redistributed to lower altitudes during the spring and early summer months. In these landscapes, surface water reserves are particularly precious, and several major rivers—such as the Columbia, Colorado and San Joaquin—are in fact *exotic* streams, transporting water from distant environs subject to higher precipitation rates. Without aqueducts and large reservoirs, it would be difficult to support large populations in the region (e.g. Los Angeles, Phoenix and Las Vegas). For these reasons, large dams and surface water reservoirs are critical to the livelihood of the Western United States.

The surface water supply index (SWSI) was developed by Shafer and Dezman (1982) for the Western United States, as a method to judge the availability of surface water supplies. The SWSI is computed for major river basins. In each basin, the typical values of four hydrologic components are used to estimate the overall abundance/deficit of surface water resources. The hydrologic variables are snowpack, precipitation, streamflow and reservoir storage, and are expressed in the following manner (Garen 1993):

$$\mathrm{SWSI} = \frac{\mathrm{aP_{snow}} + \mathrm{bP_{precip}} + \mathrm{cP_{streamflow}} + \mathrm{dP_{storage}} - 50}{12} \tag{11.6}$$

In the above equation, the *P* values are the percentiles of each hydrological variable, based on the current water conditions. The coefficients *a*-*d* are the average contributions of each component to the surface water supply, and their sum is unity. The subtraction of 50 centers the data about the median (the 50th percentile), and the division by 12 is an arbitrary scaling which produces index magnitudes that are comparable to the PDSI. In particular, it theoretically bounds the SWSI between + 4.17 and −4.17 (Garen 1993).

The SWSI undergoes different computational procedures in several Western states. For example, in the state of Colorado there are two sets of weights (i.e. values for *a*-*d*), depending upon the season, while Oregon has coefficients which change on a monthly basis. Garen (1993) thoroughly critiqued the different approaches in which SWSI is computed. He made the cogent argument that if the SWSI is intended to assess surface water supply, perhaps it makes less sense to *directly* include precipitation and snowpack, as those variables will naturally transition to surface water, but are not yet surface water. Instead, Garen (1993) recommended a revised version of the SWSI which was only dependent upon streamflow and reservoir storage, i.e. *actual* surface water. However, he does not discount the value of the four hydrologic variables of the SWSI, for they play a role in river forecasting performed by the National Weather Service of the USA. But he argued that those variables are best utilized as inputs to a hydrological model, which a hydrological drought index, such as the SWSI, surely is not.

Furthermore, Garen (1993) suggested that it makes sense to input model predictions (for future key seasons [e.g. the agricultural growing seasons which require irrigation from surface water supplies]) into the SWSI computation, rather than the actual observational data. For example, a November assessment of the current surface water supply is probably less relevant than a November prediction of the upcoming June water supply, when the surface water resources will need to be tapped to irrigate farmland.

Keyantash (2005) analysed the SWSI values for a 23-year period (1983–2005) in adjacent river basins in Oregon and Idaho; see Fig. 11.6. The climatologies of the two basins are highly similar, but different computational procedures between Oregon and Idaho resulted in somewhat dissimilar SWSI values, which had a correlation of 0.78 during the examination period. In contrast, the SPI values in the two basins exhibited a correlation coefficient of 0.93. Keyantash (2005) concluded that the inter-state comparability of the SWSI is compromised by its non-standardized computational scheme. For these complex reasons, the SWSI has not found broad adoption outside of the region for which it was developed, the Western United States.

Fig. 11.6 Malheur and Weiser basins are adjacent, with highly similar climates (i.e. temperature and precipitation patterns). Nonetheless, their SWSI values differ noticeably due to different computational rules. Modified from Keyantash 2005

11.4 Composite Drought Indices

Composite drought indices consider water deficiencies across multiple compartments of the hydrological cycle. They are germane here because they include both meteorological and hydrological droughts (as well as agricultural drought). Discussed here are two examples, the U.S. Drought Monitor and the aggregate drought index.

11.4.1 U.S. Drought Monitor (USDM)

The U.S. Drought Monitor (USDM) is a weekly drought assessment map produced by scientific experts representing several branches of the US government. This composite index has been in existence since 1999. It is a semi-quantitative analysis of drought conditions across the USA, based on multiple drought indices (such as the SPI, SWSI, PDSI and PDSI variants), percentiles from measured site data (including soil moisture and streamflow), satellite vegetative health imagery, plus field reports from over 450 observers nationwide (USDM 2020). National experts from the National Oceanographic and Atmospheric Administration (NOAA), National Centers for Environmental Prediction (NCEP), National Weather Service (NWS) and the Climate Prediction Center (CPC) weigh in on observational data during weekly meetings and collectively assess US drought conditions. Their findings are compiled into a national map for each week. The processes involved in the weekly creation of the USDM are detailed by Svoboda et al. (2002). Figure 11.7 shows a drought monitor map for US drought conditions on 18 February 2020.

The USDM drought assessments contain four categories of drought intensity, all prefixed with the letter "D" (for dry/drought):

0. Abnormally dry
1. Moderate drought
2. Severe drought
3. Extreme drought
4. Exceptional drought.

The integer ranks of these classifications were originally selected as public-friendly analogues to the familiar Fujita (tornado) and Saffir–Simpson (hurricane) intensity scales (Svoboda et al. 2002). Semi-quantitatively, these numerals can be viewed as roughly representing the integer values of the PDSI and/or SWSI. Similarly, the associated labels bear strong similarity to verbal descriptions attached to the PDSI, rainfall deciles, SPI and SWSI. However, it should be noted that the percentiles associated with the relative classifications do not perfectly match across the various indices, so the non-exceedance probabilities associated with each category should not be assumed to be identical. Svoboda et al. (2002) provide a useful comparison of the various USDM index values with the PDSI and SPI, among others.

While the drought monitor does not explicitly distinguish between agricultural, meteorological and hydrological droughts, it does so implicitly through the use of the

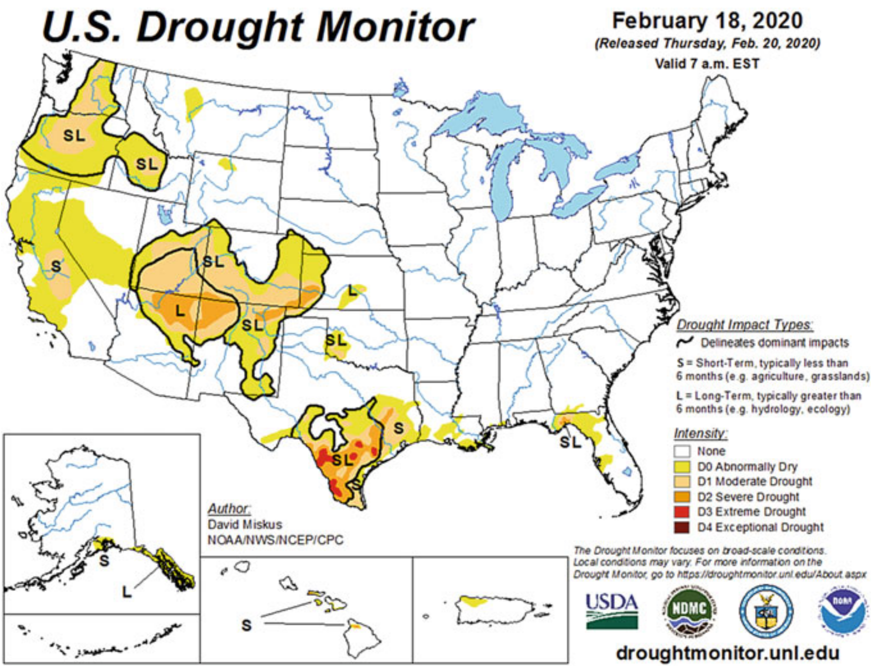

Fig. 11.7 USDM for 18 February 2020

prefixes "S" and "L" to distinguish between short- and long-term impacts, respectively. The "S" is associated with agricultural drought and the "L" with hydrological drought, and both letters could potentially imply meteorological drought, which can occur from short to long time intervals. Furthermore, both letters may appear in the same region, to indicate that there are distinct short-term and long-term drought impacts. Ultimately, USDM data is used to make national agricultural decisions in the USA on farm relief payments, farmer tax deferral decisions, livestock foraging and agricultural loans (USDM 2020).

11.4.2 Aggregate Drought Index (ADI)

The aggregate drought index (ADI; Keyantash and Dracup 2004) is a comprehensive drought index that, in the spirit of SPI, takes a standardized statistical perspective to assess drought. The ADI utilizes diverse observations of water availability in a region of hydroclimatic uniformity, such as a climate division or a river basin. It incorporates observed hydrological data from various geophysical compartments—such as precipitation, evaporation, streamflow and reservoir volume, among other possibilities (viz. soil moisture and snowpack levels; see Fig. 11.8)—to construct a multi-variate assessment of water availability. The anomalies of each variable

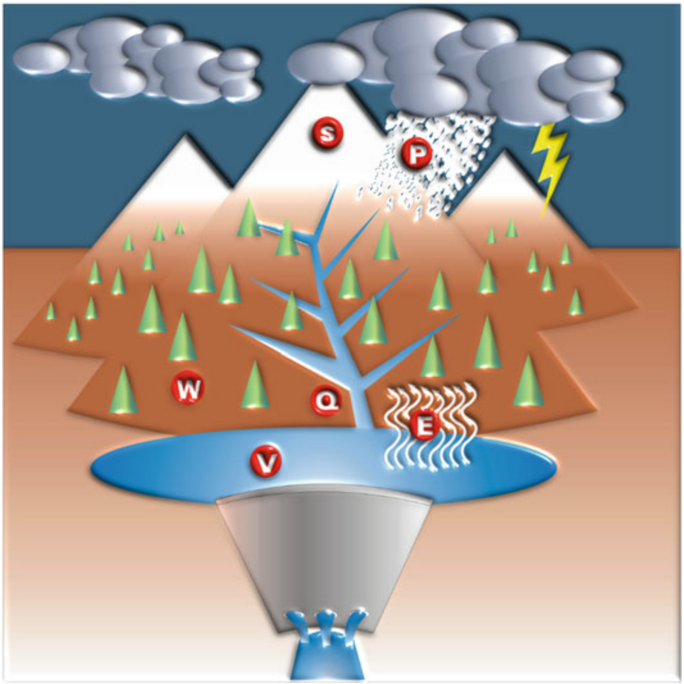

Fig. 11.8 Hydrological variables included in the ADI are precipitation (P), snowpack (s), evaporation (E), soil moisture (W), streamflow (Q), and reservoir storage (V). *Source* Keyantash and Dracup 2004

are subjected to correlation-based principal component analysis (PCA) to extract a common signal of water abundance/deficit from the suite of hydrological observations. In this manner, the ADI extracts the "essential" signal from all of these components, which are all physically related by their participation in the hydrological cycle.

In mathematical terms, the ADI is the standardized anomaly of the first PC of the hydrological data. It is given as:

$$\mathbf{a} = \frac{\mathbf{z}_1}{\sigma_{z_1}}, \quad \mathbf{z}_1 = \mathbf{X}\mathbf{e}_1 \tag{11.7}$$

where

$\mathbf{a}$ = ADI time series for select month (e.g. February)
$\mathbf{z}_1$ = first PC times series (for February)
σ_{z_1} = standard deviation of first (February) PC
$\mathbf{X}$ = (year $\times$ variable) matrix of (February) observational data, expressed as standardized anomalies (mean of zero, unit standard deviation)
$\mathbf{e}_1$ = first eigenvector of the PCA.

The ADI for a selected region is separately computed for each month in the time series (i.e. 12 separate analyses). The monthly segregation allows the observational data anomalies to be judged with respect to the hydroclimatic norm for each month. The monthly ADI values are then recombined into a single chronological time series. More detailed computational instructions are given in Keyantash and Dracup (2004).

The ADI uses only the first principal component due to the unique, advantageous properties of PCA. Principal component analysis produces an alternate expression of the original dataset, possessing as many alternate variables (known as the "principal components" [which are linear combinations of the original variables]) as the original dataset. For example, if six hydrological variables underwent PCA, there would be six created PCs. The full variance—i.e. "information"—of the original dataset is completely replicated by the PCs, with the vital distinction that the bulk of the variance is maximally apportioned to the first PC, with decreasingly less variance in subsequent PCs.

Furthermore, each PC is fully uncorrelated with every other PC (i.e. their correlation coefficients are zero), such that information expressed in one PC is not duplicated by another. Thus, PCA can be a powerful data reduction technique, as latter PCs contribute vanishingly less information to the problem at hand (in this case, water supply across the study region). In the ADI study of three climate divisions in California, Keyantash and Dracup (2004) found that the first PC described an average of 60 per cent of the variance across the 5–6 hydrological variables illustrated in Fig. 11.8 (snowpack was not relevant for all divisions).

A comparison of the ADI and SPI for the San Jacinto river basin of Southern California is shown in Fig. 11.9 for the month of September for years 1943–1998 (Keyantash and Sakata 2012). The ADI values have been composited into 12-month sums to match the 12-month timescale of the SPI (i.e. October through September).

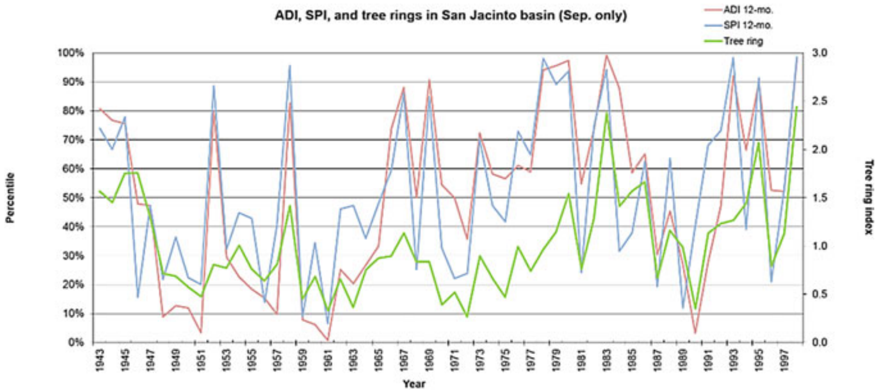

Fig. 11.9 ADI compared to the SPI and a tree ring chronology for a 12-month period, ending in September, for water years 1943–1998 in the San Jacinto river basin of Southern California. Note that the tree ring index values are not percentiles (i.e. the left ordinate is not accurate for the tree ring index). *Source* Keyantash and Sakata 2012

Due to fundamentally different index values, the ADI and SPI values are expressed as percentiles to aid comparability.

Also shown in Fig. 11.9 is a tree ring chronology of bigcone Douglas fir (*Pseudotsuga macrocarpa*) from the same basin. Low values of the tree ring index presumably indicate limited growth due to water deficiency/drought. Overall, the ADI and SPI exhibit tight correlation ($r = 0.81$) for the examined interval, and both qualitatively agree with the tree ring chronology.

Summary

Drought is a complex phenomenon to characterize. There are multiple aspects of water deficiency (such as soil moisture, rainfall and streamflow, to name a few) which are associated with different forms of drought (agricultural, meteorological and hydrological, respectively). These water shortages occur on different minimum timescales, so the lens to assess drought intensity may need to broaden or contract to discern between various drought forms. Yet these timescales may also overlap during droughts of extended duration—a region may simultaneously experience short-term and long-term drought.

Furthermore, the measure of water "deficiency" depends upon the native climate of the region. For example, drought conditions in England would bear little resemblance to a recognized drought in Australia. The anthropological demand for water is another important factor that can exacerbate the impacts of natural drought events.

These latent complexities lead to a variety of research indices to describe drought. For the sake of brevity, this chapter has focused on widely accepted drought indices for meteorological and hydrological drought. It also discussed some composite indices which jointly assess meteorological, hydrological and agricultural drought conditions.

Meteorological drought was discussed in the context of the PDSI, rainfall deciles, SPI and SPEI. Hydrological drought indices were explored through the concepts of the total water deficit and SWSI. The USDM and the ADI were introduced as examples of composite drought indices, with data for the latter being compared to the SPI and a tree ring chronology.

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