TENNESSEE REGULATORY AUTHORITY

460 James Robertson Parkway
Nashville, Tennessee 37243-0505

NOTICE OF ADMINISTRATIVE NOTICE

DOCKET: **08-00039**

IN RE: **Petition of Tennessee American Water Company to Change and Increase Certain Rates and Charges so as to Permit it to Earn a Fair and Adequate Rate of Return on Its Property Used and Useful in Furnishing Water Service to Its Customers**

DATE: **August 29, 2008**

This Notice is to advise that, pursuant to Tenn. Code Ann. § 4-5-313(6) and § 65-2-109(3), the Tennessee Regulatory Authority ("TRA") will take administrative notice of the following publications and documents in the above docket.

NARUC, Management Audit Manuals, Vol. I Fundamentals of Management Audits (Filed as Hearing Exhibit 58).

William M. Alley, *The Palmer Drought Severity Index: Limitations and Assumptions,* 23 JOURNAL OF CLIMATE AND APPLIED METEOROLOGY 1100 (1984) (Attached hereto).

Committee on USGS Water Resources Research, Water Science and Technology Board, Division on Earth and Life Studies, National Research Council, *Estimating Water Use in the United States* (2002) *available at* (http://www.nap.edu/catalog/10484.html) (Attached hereto).

Any party desiring to comment on this Notice shall file such comments with the Authority no later than Wednesday, September 3, 2008.

FOR THE TENNESSEE REGULATORY AUTHORITY,

J. Richard Collier

J. Richard Collier, Hearing Officer

cc: Parties of Record
Original in docket file

The Palmer Drought Severity Index: Limitations and Assumptions

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ABSTRACT

The structure of the Palmer Drought Severity Index (PDSI), which is perhaps the most widely used regional index of drought, is examined. The PDSI addresses two of the most elusive properties of droughts: their intensity and their beginning and ending times. Unfortunately, the index uses rather arbitrary rules in quantifying these properties. In addition, the methodology used to standardize the values of the PDSI for different locations and months is based on very limited comparisons and is only weakly justified on physical or statistical grounds. Under certain conditions, the PDSI values are very sensitive to the criteria for ending an "established" drought and precipitation during a month can have a very large effect on the PDSI values for several previous months.

The distribution of the PDSI conditioned on the value for the previous month may often be bimodal. Thus, conventional time series models may be quite limited in their ability to capture the stochastic properties of the index.

1. Introduction

Droughts are, by nature, regional phenomena. For this reason, several indicators exist that attempt to encapsulate drought severity on a regional basis. Perhaps the best known of these is the Palmer Drought Severity Index (PDSI). Palmer (1965) defined a drought period as "an interval of time, generally of the order of months or years in duration, during which the actual moisture supply at a given place rather consistently falls short of the climatically expected or climatically appropriate moisture supply". Working from this definition, Palmer (1965) developed the PDSI as a means of measuring the severity of drought. This index has also been referred to as simply the Palmer Index, since it also evaluates wet situations. However, here interest is centered on droughts, and the index will be referred to as the PDSI.

The PDSI is widely used. For example, during the growing season values of the PDSI for climatic divisions of the United States are shown in the *Weekly Weather and Crop Bulletin*, published jointly by the U.S. Departments of Commerce and Agriculture. The index has also been used by various researchers to illustrate the areal extent and severity of drought in the northeastern United States during the early to mid-1960s (Palmer, 1967) and across the United States during the hot, dry summer of 1980 (Karl and Quayle, 1981). Felch (1978) used the PDSI to compare droughts of the 1930s, 1950s and mid-1970s across the continental United States. Lawson *et al.* (1971) studied the spatial and temporal characteristics of droughts in Nebraska using the PDSI. Dickerson and Dethier (1970) applied the PDSI for determining the frequencies of various drought severities in the northeastern United States. Eigenvector analyses of PDSI values have been made for 53 climatic divisions of the upper Midwest (Klugman, 1978) as well as for the entire United States for the years 1931–40 (Skaggs, 1975). Karl and Koscielny (1982) and Diaz (1983) used the PDSI to study the spatial and temporal characteristics of dry and wet episodes over the contiguous United States during 1895–1981. Kappel (personal communication, 1983) used PDSI maps from April 1975 to July 1976 to develop a crude relationship between areas of drought and increasing fire danger in Minnesota and Wisconsin during 1976. Puckett (1981) reconstructed a 230-year record of the PDSI for northern Virginia using a relationship with variations in the widths of tree rings.

Although referred to as an index of meteorologic drought, the method takes into account precipitation, evapotranspiration and soil moisture conditions, all of which are determinants of hydrologic drought. Fieldhouse and Palmer (1965) note that the PDSI should be related to water supplies in streams, lakes and reservoirs and hence be of interest to hydrologists as well as to meteorologists and climatologists. Bowles *et al.* (1980) used the PDSI to evaluate indices they developed for three municipal and three irrigation water supply systems in Utah.

An areal study of droughts generally requires an "objective" index of drought severity. The PDSI is one of the few general indices of drought readily available and is standardized to facilitate direct comparisons of PDSI between different regions. Hence, as referenced above, the method has been used extensively in the literature. Karl (1983) examined the sensitivity of the spatial characteristics of drought duration indicated by the PDSI to values of available water capacity and weighting factors used in the index. However, no overall examination has been made of the structure of the method. Here, the procedure for computing the Palmer Drought Severity Index will be discussed, followed by a critique of the method. The computational procedure will be described in detail, in part because it is usually (if not always) glossed over in descriptions of the method, and in part because it will help illustrate some of the deficiencies in the method which have not been well documented.

2. The computational procedure

Palmer's method begins with a water balance (usually on a monthly or weekly basis) using historic records of precipitation and temperature. Soil moisture storage is handled by dividing the soil into two layers and assuming that 25 mm of water can be stored in the surface layer. The underlying layer has an available capacity that depends on the soil characteristics of the site being considered. Moisture cannot be removed from (recharged to) the underlying layer until all of the available moisture has been removed from (replenished in) the surface layer. Potential evapotranspiration (PE) generally is computed using Thornthwaite's method (Thornthwaite, 1948). Evapotranspiration losses from the soil occur if $PE > P$, where P is precipitation for the month. Evapotranspiration loss from the surface layer L_s is assumed to take place at the potential rate. It is assumed that loss from the underlying layer L_u depends on initial moisture content in the underlying layer, potential evapotranspiration and the combined available moisture capacity (AWC) in both soil layers. That is, if $PE > P$,

$$L_s = \min[S_s, (PE - P)],$$

$$L_u = [(PE - P) - L_s]S_u/AWC, \quad L_u \leq S_u,$$

where P is the precipitation and S_s and S_u are the amounts of available moisture stored at the beginning of the month in the surface and underlying layers respectively. Runoff is assumed to occur if and only if both layers reach their combined moisture capcity AWC.

As part of the water balance, Palmer's method computes three additional terms: potential recharge, potential loss and potential runoff. Potential recharge (PR) is defined as the amount of moisture required to bring the soil to field capacity:

$$PR = AWC - (S_s + S_u). \tag{1}$$

Potential loss (PL) is defined as the amount of moisture that could be lost from the soil to evapotranspiration provided precipitation during the period was zero:

$$PL = PL_s + PL_u, \tag{2}$$

where

$$PL_s = \min(PE, S_s),$$

$$PL_u = (PE - PL_s)S_u/AWC, \quad PL_u \leq S_u.$$

Potential runoff (PRO) is defined as potential precipitation minus potential recharge. Palmer (1965) assigned potential precipitation as being equal to AWC. Thus,

$$PRO = AWC - PR = S_s + S_u. \tag{3}$$

Palmer (1965) recognized that "this is not a particularly elegant way of handling this problem" and noted that were he to redo his analyses he would redefine potential precipitation as some value such as three times the normal precipitation for the month. This would remain a fairly arbitrary approach but would at least recognize that precipitation and available water capacity are unrelated terms.

The four potential values—PE, PR, PL and PRO—are used to compute four coefficients which are dependent on the climate of the area being analyzed:

$$\alpha_j = \overline{ET}_j/\overline{PE}_j,$$

$$\beta_j = \bar{R}_j/\overline{PR}_j,$$

$$\gamma_j = \overline{RO}_j/\overline{PRO}_j,$$

$$\delta_j = \bar{L}_j/\overline{PL}_j, \quad j = 1, \ldots, 12, \tag{4}$$

where the overbars refer to the fact that the coefficients are computed using average values for month j. A separate set of coefficients is determined for each of the 12 months.

These coefficients are used to compute the differences d for each month between the actual precipitation for the month P and the "CAFEC" (Climatically Appropriate For Existing Conditions) precipitation $\hat{P}$ such that

$$\begin{aligned} d &= P - \hat{P} \\ &= P - (\alpha_j PE + \beta_j PR + \gamma_j PRO - \delta_j PL). \end{aligned} \tag{5}$$

The definition of $\hat{P}$ in Eq. (5) is analogous to a simple water balance where precipitation is equal to evapotranspiration plus runoff (and ground-water recharge) plus or minus any change in soil-moisture storage. A "moisture anomaly index" Z, is defined as

$$Z = K_j d, \tag{6}$$

where K_j is a weighting factor defined as

$$K_j = 17.67\hat{K}_j / \sum_{i=1}^{12} \bar{D}_i \times \hat{K}_i, \quad j = 1, \ldots, 12, \tag{7}$$

where $\bar{D}_j$ is the average of the absolute values of d for month j and

$$\hat{K}_j = 1.5 \log_{10}\left(\frac{T_j + 2.8}{\bar{D}_j}\right) + 0.50, \qquad (8)$$

where

$$T_j = (\overline{PE}_j + \bar{R}_j + \overline{RO}_j)/(\bar{P}_j + \bar{L}_j).$$

The parameter T_j is a measure of the ratio of "moisture demand" to "moisture supply" for the month and region. The purpose of the weighting factors is to adjust the departures from normal precipitation d such that they are comparable among different areas and for different months. For example, ideally $Z = -4.0$ during July in Oklahoma is equivalent to $Z = -4.0$ during February in Virginia in terms of a moisture departure from "climatically normal conditions for the month. Weighting factor K_j tends to be large in arid regions and small in humid regions. During the derivation of K_j, Palmer (1965) assumed that the economic consequences of the driest year in one place were the same as those of the driest year in other places. The influence of large-scale changes in water usage such as those resulting from reservoir development, urbanization or changes in irrigation practices are ignored. Eqs. (7) and (8) were derived using data from nine areas of the United States. Their complexity and unusual form result from the difficulty Palmer had in deriving them.

The moisture anomaly index Z thus expresses a relative departure of the weather of a particular month and location from the average moisture conditions of that month. Palmer (1965) evaluated the accumulation of the moisture anomaly index Z for

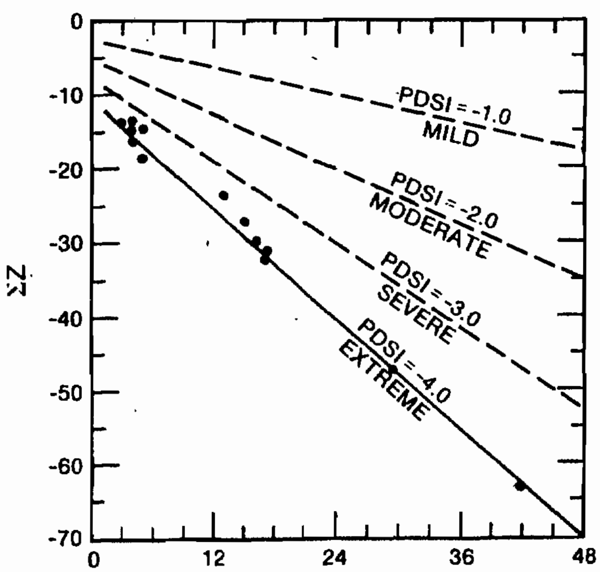

FIG. 1. Accumulated values of the moisture anomaly index Z during the driest periods of various lengths in central Iowa and western Kansas (after Palmer, 1965).

TABLE 1. Classification of recent weather according to PDSI (X).

X	Class
≥4.00	Extremely wet
3.00 to 3.99	Very wet
2.00 to 2.99	Moderately wet
1.00 to 1.99	Slightly wet
0.50 to 0.99	Incipient wet spell
0.49 to −0.49	Near normal
−0.50 to −0.99	Incipient drought
−1.00 to −1.99	Mild drought
−2.00 to −2.99	Moderate drought
−3.00 to −3.99	Severe drought
≤ −4.00	Extreme drought

the 13 driest intervals in his two original study areas (central Iowa and western Kansas) and noted that they plotted as a straight line on a graph of accumulated Z versus length of dry period as shown in Fig. 1. He defined these dry periods as extreme drought and assigned a numerical drought severity value of PDSI = −4.0 to an "eyeball-fit" line through the 13 points of Fig. 1. He then subdivided the region between extreme drought and an accumulated Z of zero by three lines which he arbitrarily defined as the upper limits of "severe drought" (PDSI = −3.0), "moderate drought" (PDSI = −2.0) and "mild drought" (PDSI = −1.0). Palmer's complete classification of droughts is included in Table 1. Note that by reversing signs, similar definitions were developed for wet spells.

Based on Fig. 1, drought severity for the ith month, $X(i)$, can be described by

$$X(i) = \sum_{t=1}^{i} Z(t)/(2.691 + 0.309i). \qquad (9)$$

Note that there appears to be a slight typographical error in Eq. (9) as it is shown on page 21 of Palmer (1965). Unfortunately, Eq. (9) gives the same weight to moisture deficiencies that occurred several months ago as it does to moisture deficiencies of the most recent month. Palmer (1965) suggested that a more appropriate index would be of the form

$$X(i) = Z(i)/3 + cX(i - 1). \qquad (10)$$

Note that Eqs. (9) and (10) are equivalent for the first month of a dry spell $[X(i - 1) = 0]$. Palmer (1965) determined c to be 0.897. This value of c maintains X at a given level from month to month for rates of Z accumulation that maintain a drought of constant severity in Fig. 1. Palmer's final expression for drought severity is

$$X(i) = 0.897X(i - 1) + Z(i)/3, \qquad (11)$$

where $X(i)$ is the value of the PDSI for the ith month.

After a dry spell, consistently normal or wet weather will eventually result in values of X computed using

Eq. (11) approaching zero. However, Palmer (1965) found this requirement to be too stringent for the termination of a drought. In addition, application of Eq. (11) requires identification of the initial month of a dry spell. Similar conclusions were reached for wet spells. Palmer was therefore confronted with the problem of establishing the beginning and end of a drought or wet spell. His solution was to use separate bookkeepings and Eq. (11) to keep track of three indices defined as follows:

X_1 = severity index for a wet spell that is becoming "established,"

X_2 = severity index for a drought that is becoming "established,"

X_3 = severity index for any wet spell or any drought that has become "established."

The variable X_1 is restricted to nonnegative values and X_2 to nonpositive values. The values of X_1 and X_2 are set to zero when computations of Eq. (11) violate these restrictions. A drought is considered established when $X_2 \leqslant -1.00$ for the first time since a previously established drought or wet spell has ended. A wet spell is considered established when $X_1 \geqslant 1.00$ for the first time since a previously established drought or wet spell has ended. At these times, $X_3 = X_2$ for an established drought or $X_3 = X_1$ for an established wet spell. An established drought or wet spell is considered to definitely end when the index reaches the "near normal" category which lies between -0.50 and $+0.50$. At this point, X_3 returns to zero. The termination of an established drought is assumed to occur when $Z(i) \geqslant Z_e(i)$ where

$$Z_e(i) = -2.691X_3(i-1) - 1.5, \qquad (12)$$

where $Z_e(i)$ is the moisture required to reduce the severity of an established drought to -0.50 in a single month. Similarly, the termination of an established wet spell is assumed to occur when $Z(i) \leqslant Z_e(i)$ where, in this case,

$$Z_e(i) = -2.691X_3(i-1) + 1.5. \qquad (13)$$

Eqs. (12) and (13) are derived by solving for $Z(i)$ in Eq. (11) and substituting -0.50 and 0.50, respectively, for $X(i)$. Rather than simply using Eqs. (12) or (13) to determine whether an established drought or wet spell has ended, Palmer (1965) relies on the computation of a "percentage probability" that an established drought or wet spell has ended where

$$P_e(i) = \frac{100 \sum_{j=0}^{j^*} U(i-j)}{Z_e(i) + \sum_{j=1}^{j^*} U(i-j)}, \qquad (14)$$

where $0 \leqslant P_e(i) \leqslant 100$. It is important to note, as Palmer did, that P_e is not really a probability in the conventional sense but rather a measure of the ratio of moisture received to that required to end an established drought or wet spell. The definition of $U(i)$ depends on whether a drought or wet spell has been established. In the case of an established drought, Palmer (1965) notes that a value of $Z = -0.15$ will maintain an index of -0.50 from month to month. Therefore, any value of $Z \geqslant -0.15$ will tend to end a drought, and he defines $U(i)$ as

$$U(i) = Z(i) + 0.15. \qquad (15)$$

After a drought has become established ($X \leqslant -1.00$), Eq. (15) applies to the first month having $Z \geqslant -0.15$ and is computed for each successive month until the computations show a value of P_e equal to either 0 or 100. The parameter j^* in Eq. (14) corresponds to the number of successive values of $U(i)$ computed immediately prior to the current month. Similar computations are performed to evaluate P_e for an established wet spell except in this case

$$U(i) = Z(i) - 0.15.$$

There is an inconsistency in the use of Eq. (14) to indicate the end of a drought or wet spell. This occurs because Eq. (14) may indicate that a drought has ended $[P_e(i) = 100]$ even though $Z(i) < Z_e(i)$. To illustrate this inconsistency, first note that $P_e(i)$ in Eq. (14) will equal or exceed 100 whenever

$$U(i) \geqslant Z_e(i). \qquad (16)$$

Substituting Eq. (15) into (16) yields

$$Z(i) \geqslant Z_e(i) - 0.15,$$

as the criterion resulting from Eq. (14) for ending an established drought, rather than $Z(i) \geqslant Z_e(i)$. Likewise, Eq. (14) may indicate an established wet spell has ended even though $Z(i) > Z_e(i)$.

The drought index X for a particular month is set equal to X_1, X_2, or X_3. Often only one of these three indices is nonzero, and X is set to the nonzero index. However, many conflicting cases can arise and the appropriate index to use for X is not always obvious. For example, it is common for both wet spells ($X_1 > 0$) and dry spells ($X_2 < 0$) to be simultaneously indicated as becoming established. It is also common for a situation such as $X_1 \geqslant 1.00$ and $X_3 \leqslant -1.00$ to occur simultaneously.

In order to select the appropriate value of X when the choice of index is not obvious, Palmer devised a set of operating rules that rely heavily on computing values of X_1, X_2 and X_3 over several months and then backtracking based on the direction in which the weather appeared to be going. An example of the selection procedure is shown in Table 2. First, observe how the values of X_3 were assigned. The negative values of X_3 indicate that an "established drought" occurred for December 1931–October 1932. Eq. (11)

TABLE 2. Palmer Drought Severity Index for Washington, DC, December 1931–December 1932.

Month	Z	P_e	X_1	X_2	X_3	X	X^{*a}
December	−2.75	0.0	0.0	0.0	−4.75[b]	−4.75	−4.75
January	0.36	4.5	0.12	0.0	−4.14	0.12	−4.14
February	−0.51	1.5	0.0	−0.17	−3.88	−0.17	−3.88
March	3.83	45.4	1.28	0.0	−2.20	1.28	−2.20
April	−0.89	39.6	0.85	−0.30	−2.27	0.85	−2.27
May	1.15	58.6	1.15	0.0	−1.66	1.15	−1.66
June	−0.34	58.9	0.91	−0.11	−1.60	−0.11	−1.60
July	−1.41	44.5	0.35	−0.57	−1.90	−0.57	−1.90
August	−2.89	7.5	0.0	−1.47	−2.67	−1.47	
September	0.05	11.5	0.02	−1.30	−2.38	0.02	
October	4.12	88.9	1.39	0.0	−0.76	1.39	
November	4.08	100.	2.61	0.0	2.61	2.61	
December	1.88	0.0	0.0	0.0	2.97	2.97	

[a] Values for X if P_e = 0.0 for August.
[b] Values of X_1, X_2 and X_3 chosen for X are underlined.

was used recursively to compute these values. Then, in November, the large value of $Z = 4.08$ resulted in $P_e = 100$, i.e., a definite end to the established drought. Because $X_1 \geqslant 1.00$, November also marked the beginning of an established wet spell which continued in December. Now observe how the values of X were assigned. Since X_3 for December 1931 was negative and $P_e = 0.0$, X was set equal to X_3. However, $0 \leqslant P_e < 100$ in January and the method did not originally assign $X = X_3$. Values for X were not assigned until P_e reached 100 in November at which point $X = X_3 = X_1 = 2.61$. The method then backtracked from November through January using the following rules:

(i) assign $X = X_1$ until $X_1 = 0$;
(ii) then assign $X = X_2$ until $X_2 = 0$;
(iii) repeat steps (i) and (ii) until a month was reached which already had an X value assigned, i.e., December 1931.

If P_e returns to zero during an established drought or wet spell, then $X = X_3$ for all values of X between and including the months during which $P_e = 0.0$. For example, X^* shows the values of X for December–July if P_e for August 1932 had been zero. The values of X^* differ substantially from those of X. The value of PDSI for January changes from "near normal" to "extreme drought" and the PDSI for March from "slightly wet" to "moderate drought."

Whenever a drought or wet spell has become "established" and $0 < P_e < 100$, a value for the PDSI can not be assigned until P_e reaches 0 or 100. This obviously causes problems when the PDSI is used in an operational mode (calculated in real time). Values in the *Weekly Weather and Crop Bulletin* circumvent this problem, by letting $X = X_3$ whenever $0 < P_e \leqslant 50$ and letting either $X = X_1$ or $X = X_2$, whichever results in an index having the opposite sign of X_3, whenever $50 < P_e < 100$ (T. Heddinghaus, personal communication, 1983). Other backtracking problems are resolved by selecting the PDSI as X_1 or X_2, whichever has the largest absolute value, whenever X_3 equals zero.

3. A critique

Felch (1978) notes that there are people who oppose development of a drought index on the grounds that the problem is much too complex to take full account of all the pertinent physical and biological factors. It is not the purpose of this paper to address this issue. The PDSI is probably the most widely used drought index and therefore an understanding of its properties and assumptions is important.

From the preceding description it should be evident that computations of the PDSI are quite involved. A number of arbitrary assumptions were required during development of the method, and it uses several unfamiliar terms and definitions.

The backbone of the method is a water balance computation. There are several limitations involved in using water balance models (Alley, 1984). The first is that there is no universally accepted method of computing potential evapotranspiration. The method of Thornthwaite (1948) has typically been used; however, other applicable methods could be employed. The water balance model assumes that the capacities of the two soil layers are independent of seasonal or annual changes in vegetation cover and root development. These temporal changes are particularly important in cultivated areas.

Most water balance models assume that evapotranspiration for a period is equal to the potential evapotranspiration whenever $P \geqslant PE$. However, precipitation and evapotranspiration often are distributed within a month or week in such a way that both periods of deficiency and surplus can occur. Particularly in late summer, simulated soil moisture at the beginning and end of the month may be very low. Yet, if $P \geqslant PE$, the model erroneously assumes evapotranspiration occurs at the potential rate for the entire month.

When $P < PE$ and soil-moisture deficits develop, almost all water balance models invoke some limitation on evapotranspiration as a function of soil-moisture content. The availability of soil moisture for plant growth over the range from field capacity to permanent-wilting point has been treated by a wide range of techniques. At one end of the spectrum, Veihmeyer and Hendrickson (1955) suggested that, in some cases, evapotranspiration may proceed at the potential rate until soil moisture approaches the permanent-wilting point. On the other hand, Thornthwaite and Mather (1955) assume the ratio of actual to potential evapotranspiration is a linear function of the ratio of available soil moisture to the available water capacity. The true relationship between actual and potential evapotranspiration will vary with rooting characteristics, soil texture and plant physiology, as well as the rate of evapotranspiration itself and climatological conditions. In the absence of a generally applicable physical model, several compromises have been made between the above two models. Most of these assume that evapotranspiration occurs at close to the potential rate until some proportion of the available water is depleted, after which the actual evapotranspiration rate is less than the potential rate. Palmer's approach is one of these compromises.

The universal designation of 25 mm as the moisture capacity of the surface layer from which evapotranspiration takes place at the potential rate seems rather arbitrary, although others have also made this assumption (see Haan, 1972). Palmer's model uses an analog of the linear approach of Thornthwaite and Mather (1955) to estimate evapotranspiration from the underlying layer. Another approach is to simply assume evapotranspiration losses from the underlying layer are equal to some percentage (often on the order of 10%) of the potential loss (for example, see Calder *et al.*, 1983; Rushton and Ward, 1979). The 25 mm moisture capacity of the surface layer is small compared to monthly values of $(PE - P)$, often observed in many climates, and the simulated soil-moisture storage in the upper layer often goes from full to empty in a single month. The assumed moisture capacity of the underlying layer is often much greater than 25 mm and, thus, after moisture is completely withdrawn from the surface layer the simulated rate of evapotranspiration will often be close to the potential rate. For these reasons, the water balance computations often are insensitive to the inclusion of the surface layer.

Perhaps the most serious deficiencies in the water balance computations are related to the estimation of runoff. Apparently Palmer's runoff term includes both recharge to ground water and overland runoff. No lag is incorporated in the Palmer model to account for the delay between generation of excess water and its appearance as runoff. In particular applications Thornthwaite and Mather (1955) and Mather (1981) suggest that, when using water balance models, approximately 50–75% of the "runoff" should be delayed each month in order to reproduce monthly flow volumes observed in streams. Of course, the fraction held back should vary with the depth and texture of the soil, physiography, size of the basin and nature of the ground-water system.

The Palmer model is a "threshold-type" model in that it assumes that runoff does not occur until the soil-moisture capacity of the upper and lower layers is filled. The limitations of this assumption have been recently reviewed by Morton (1983). Rushton and Ward (1979) found that monthly water balances lead to recharge (runoff) values which are up to 25% less than those from daily water balances, and that threshold-type models tend to underestimate recharge (runoff) during the summer and early autumn. This suggests some inconsistency in performing the PDSI computations using the same parameters for both weekly and monthly computations. The temporal aggregation of precipitation over a month (week) and the simplified treatment of runoff result in end-of-month (week) soil-moisture storage simulated by the Palmer model being more often than not at its capacity AWC for many regions. This is an unrealistic approximation. This limitation may be more important for those studies that rely heavily on a given PDSI for a specific month during a given year.

Although the PDSI is often reported for all parts of the United States and has been used on a nationwide basis and in the northern parts of the United States to examine temporal and spatial patterns of drought (e.g., see Dickerson and Dethier, 1970; Skaggs, 1975; Klugman, 1978; Karl and Koscielny, 1982), the method makes no allowance for the effect of snowmelt or frozen ground. Thus, it may provide misleading results in the northern or mountainous parts of the United States.

Although one should be aware of the limitations of the water balance model used in determining the PDSI, there are other features of the method which are perhaps more troublesome. Perhaps the most serious potential problem with the PDSI is the arbitrary designation of drought severity classes. An index value of -4.0 was defined as equivalent to extreme drought in the derivation of Eq. (11). Palmer (1965) then arbitrarily designated -3.0 as the upper limit of severe drought, -2.0 as the upper limit of moderate drought, and -1.0 as the upper limit of mild drought. It should be noted that Eq. (11) was derived using records from only central Iowa and Kansas.

In applying his method to long records in western Kansas, central Iowa and northwestern North Dakota, Palmer found that from 11 to 16% of the months were classified as severe or extreme drought and 32 to 42% of the months were classified as mild drought or drier. Fieldhouse and Palmer (1965) reported monthly values of PDSI for 1929–63 for 58 climatic divisions in the northeast United States. Approximately half of the months were classified as incipient to extreme drought ($X \leqslant -0.50$), with about 18% of the months classified as moderate to extreme drought. These results suggest that terms such as "severe" and "extreme" may be rather loosely defined by the PDSI. In any event, care should be used when referring to the drought severity classes.

Palmer attempted the difficult task of creating a drought index that is comparable between different months and different regions. An attempt was made to create a physically-based weighting factor as evidenced by the fact that T_j is the ratio of average moisture demand to average moisture supply for month j. However, Eqs. (7) and (8) are based on results from only nine climatic divisions. They were derived largely using data aggregated on the annual level; thus, their use to adjust the monthly values may not yield the desired result of comparability of the index values between months. Essentially, Eq. (8) was derived in an attempt to produce PDSI values corresponding to extreme drought ($X = -4.0$) for the driest 12-month interval in each of the nine climatic divisions. The adjustment to $\hat{K}_j$ reflected in Eq. (7) was then made such that the average annual sum of the weighted average departures ($\Sigma\bar{D}_i \times \hat{K}_j$) was the same for all nine climatic divisions. The adjustments do not provide much assurance that comparability of the PDSI exists among different regions over the range of values which the PDSI can take on. Sensitivity analyses by Karl (1983) suggest that the magnitudes of individual PDSIs are very sensitive to K_j, but overall the durations of droughts of various magnitudes are relatively insensitive.

An alternate approach would have been to simply rank the PDSI values obtained during the base period for a particular month. For example, the PDSI for January 1954 would be ranked with all other Januarys during the base period, assigning a rank of one to the lowest value, two to the second lowest, etc. The PDSI computations can then be carried out for the period of interest and the PDSI values converted to an equivalent rank (through interpolation, if necessary) during the base period. This rank would be the drought index. This would avoid the use of K_j and would provide an index of drought severity without arbitrarily defining classes such as "extreme drought." Occasionally, a value of PDSI would be outside the range of values for that month of the year computed during the base period, and it will be difficult to assign a rank. Extension of the base period to the present time would eliminate this problem. This approach, without the extended base period, can be applied to the PDSIs as currently calculated.

As illustrated in Table 2, values of the PDSI can change abruptly from one month to the next. It is not unlikely for the method to indicate a month of "moderate to extreme drought" ($X \leqslant -2.0$) followed by a month of "wet" conditions ($X \geqslant 1.0$). This is not unrealistic and the method would be fallacious if this never occurred. However, the effect on the PDSI values of precipitation that occur several months later, and the somewhat arbitrary rules which control these effects, are disturbing.

Large transitions in the drought index result from the transition values of −1.0, −0.5, 0.5 and 1.0. These transition values were chosen by Palmer (1965) somewhat arbitrarily. A drought or wet spell is assumed to be established and the computations of X_3 begin when $X_2 \leqslant -1.0$ or $X_1 \geqslant 1.0$, so long as another drought or wet spell is not already established. At this point $P_e = 0.0$. A drought or wet spell is assumed no longer to be established, and the computations of X_3 end when $X_3 \geqslant -0.5$ or $X_3 \leqslant 0.5$. At this point $P_e = 100$ (although as previously noted there is a slight discrepancy between P_e and the −0.5 or 0.5 transition values). Here the −1.0 and 1.0 transition values are referred to as the "beginning values" and the −0.50 and 0.50 transition values are referred to as the "ending values."

The number of months of PDSI values in different drought severity classes during 1931–80 is shown in Table 3 for climatic division 2 of New Jersey. This division was selected randomly for illustrative purposes, but it is a climatic division for which water balance models have often been applied and developed. Results for PDSI values based on different beginning and ending values are also shown. The beginning values have little influence on the simulated values of PDSI. For example, halving the beginning values to $X_2 \leqslant -0.5$ and $X_1 \geqslant 0.5$ resulted in values of PDSI that were the same for most months, and approximately the same number of months were contained in different drought severity classes.

The transition values indicating an end to an established drought or wet spell (ending values) have a larger influence on the PDSI. For example, a relatively large change in the number of months in various drought severity classes results from simply changing the ending values to $X_3 \geqslant -0.40$ and $X_3 \leqslant 0.40$. As illustrated earlier in Table 2, the ending criteria control the timing and occurrence of abrupt changes in the PDSI. For example, the PDSI values during 1946–50 are shown in Fig. 2 along with the values that would be obtained if the ending criterion was 0.40 rather than 0.50. There were two short periods for which the revised program resulted in later transitions from an established drought and very different values of PDSI. After several months, the revised program returned to PDSI values that were the same as the original version. Similar results were obtained in sensitivity analyses of other climatic divisions in New Jersey and Nebraska.

The occasional abrupt transitions of the PDSI values affect the development of stochastic models of the index. Time series models have been fit to PDSI

TABLE 3. Sensitivity of occurrence of drought to some assumptions of the PDSI.

PDSI modification	Number of months of PDSI in given range 1931–80: −1.99 to −1.00 (mild drought)	−2.99 to −2.00 (moderate drought)	−3.99 to −3.00 (severe drought)	≤ −4.00 (extreme drought)
None	87	67	17	20
Drought or wet spell established when $X_2 \leq -0.50$ or $X_1 \geq 0.50$ respectively	84	68	17	20
Established drought or wet spell ends when $X_3 \geq -0.40$ or $X_3 \leq 0.40$ respectively	95	76	19	19
Base period is 1951–80	93	52	15	10

values by Havens *et al.* (1968), Davis and Rappaport (1974) and Katz and Skaggs (1981). The latter examined autoregressive-moving average (ARMA) models of various orders for 344 climatic divisions and found that, based on the Bayesian Information Criterion of Schwarz (1978), an AR(1) model was preferred for about 90% of the divisions. Eq. (11) suggests that an AR(1) model might be appropriate. However, the switching among X_1, X_2 and X_3 as the value of PDSI may cause problems in the ARMA representation of a PDSI time series. In particular, for an established drought with $X(i) = X_3(i)$, the PDSI for the following month, $X(i+1)$, may be either $X_3(i+1)$ or $X_1(i+1)$. If set to $X_3(i+1)$, then $X(i+1)$ will be computed using $X_3(i)$ in Eq. (11) and will probably not deviate much from $X(i)$. On the other hand, if set to $X_1(i+1)$, then $X(i+1)$ will be positive and will be much different from $X(i)$. Similar results occur for established wet spells. The result is that the conditional distribution of $X(i+1)$ given $X(i)$ tends to be bimodal during periods of "established" droughts or wet spells. This is illustrated in Fig. 3 for various ranges of $X(i)$. The tendency for a bimodal conditional distribution for $X(i+1)$ given $X(i)$ may cause problems in representing a PDSI time series as an ARMA process or in using PDSI as a predictor variable for streamflow. Karl (1983) also notes that only PDSIs computed on an operational basis should be used in studies attempting to demonstrate forecast skill, because the selection of X_1, X_2 or X_3 as X for the regular PDSI is often based on events occurring in subsequent months.

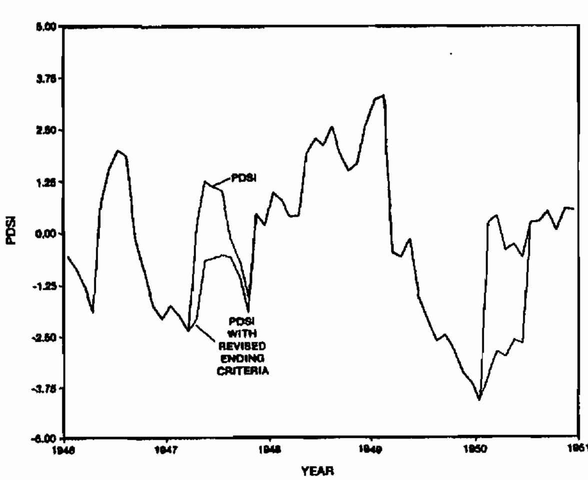

FIG. 2. Effect on PDSI values of changing ending criteria for established drought from $X_3 \geq -0.50$ to $X_3 \geq -0.40$ (1946–51 for climatic division 2 of New Jersey).

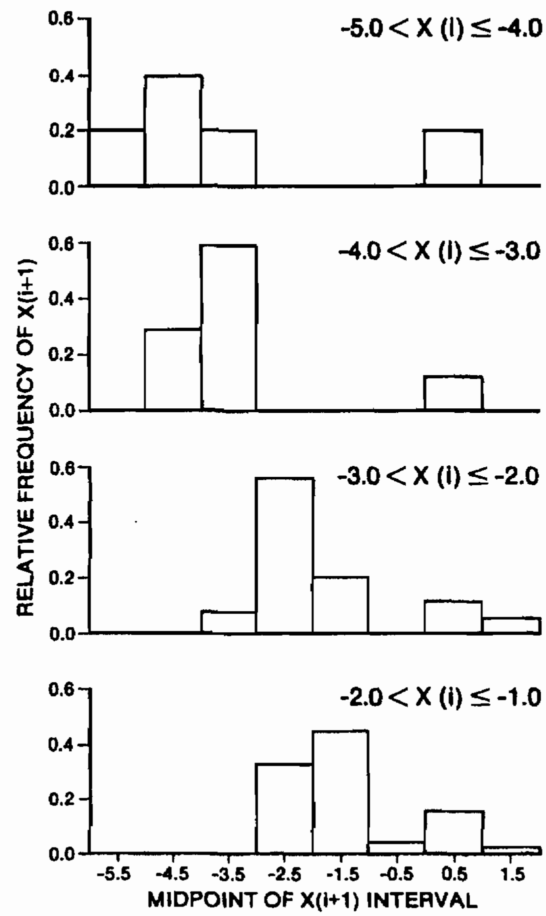

FIG. 3. Histogram of relative frequency of the PDSI for the $(i+1)$st month, $X(i+1)$, conditioned on four different intervals of $X(i)$ (New Jersey climatic division 2).

The Palmer method was developed and, to the author's knowledge, is often applied using the base period 1931–60 to estimate the weighting factors and parameters of Eq. (5). The effect of using the period 1951–80 as the base period is shown in Table 3. Fewer months are designated as moderate to extreme drought when using this more recent period as the base period, probably because the years 1951–80 contain the critical drought period of this century for New Jersey: the early to mid-1960s. There is some rationale for using either the more recent 1951–80 period or a longer period such as 1931–80 as the base period. The results of Table 3 suggest that there could be fairly large differences in results.

4. Ramifications for drought indices based on water balances

Regional drought indices on the scale of climatic divisions or states can be useful for several purposes. One of these is to provide decision makers with an overview of the relative degrees of abnormality of recent weather throughout the United States. A second and related purpose is to place current conditions in historical perspective. Karl and Quayle (1981) provide an example of this application using the PDSI. As another example, if reservoir storages in an area become very low, and yet the relevant drought index indicates only moderate drought, then this suggests that the present supply system is very vulnerable to drought. Regional drought indices may also have limited usefulness for forecasting variables such as short-term forecasts of irrigation requirements and longer term forecasts of crop production. Finally, these indices may be useful for characterizing the spatial and temporal features of historical dry episodes over large regions. Karl and Koscielny (1982) and Diaz (1983) provide examples of this application using the PDSI.

The PDSI is an attempt to use a simple water balance model as the basis for developing a regional drought severity index. In developing his drought index, Palmer was confronted with a need to provide appropriate weighting of antecedent conditions with current conditions and to provide rules for determining the beginning and end of "established" droughts. These issues are not trivial. For example, in a compendium on North American droughts, Rosenberg (1978) notes that "fully half of the contributors complained that drought is a non-event and bemoan the fact that, because of this peculiar characteristic of drought, it is difficult to know when to take action and what action to take."

Palmer (1965) describes his index as a meteorological drought index but makes a number of references to agricultural and hydrologic drought. His index is not related to specific impacts of droughts. Unfortunately, it is difficult to separate factors such as beginning and end of droughts, appropriate weighting of antecedent conditions and drought severity from specific impacts and their economic consequences. Future development of drought indices should begin with a clear definition of the nature and type of drought to which the index is addressed. The question then arises, "Are water balance models an appropriate vehicle for developing such drought indices?"

There are advantages of drought indices based on simple water balance models. They can be applied throughout the United States (with perhaps some modifications for snow and/or frozen ground), and they consider both precipitation and temperature and their combined influences on evapotranspiration, soil moisture and runoff.

On the other hand, there are inherent disadvantages based on the water balance model's simplistic representation of hydrologic phenomena, especially runoff. The simulation of runoff by a water balance model is very crude, and it is difficult to account for the lag between moisture surplus and streamflow. An alternative source of information on surface runoff conditions are index streamflow-gaging stations which are used in the monthly publication *National Water Conditions* (U.S. Geological Survey, 1984). These stations have relatively long periods of record and represent relatively natural conditions. Drought indices could be developed that rely on the flows themselves or on a suitable transformation to account for a specified level of development.

Direct measurements of other variables including soil moisture and evapotranspiration are more problematic. These are areas for which water balance models may be useful in developing indices of drought. For example, Thomas *et al.* (1983) suggest that the impact of a succession of dry years on basin biota can be assessed more accurately by deviations from norms of evaporation and residual moisture than by deviations from mean annual rainfall or runoff. However, extreme caution should be exercised in using water balance variables such as soil moisture and evapotranspiration in developing indices of drought. These variables may or may not be properly simulated by a water balance model. For example, for many regions the end-of-month (week) soil-moisture storage may be unrealistically simulated by the Palmer model as more often than not at its capacity, AWC. This is an unrealistic approximation.

More information is needed on the relationship between variables simulated by water balance models and actual physical conditions and economic consequences. Without this information it is difficult to derive drought indices not based on relatively arbitrary operating rules. In the meantime, studies of the spatial and temporal characteristics of drought which use indices based in part on a water balance model should include sensitivity analysis to test the robustness of their conclusions to somewhat arbitrary assumptions used in the development of the index.

5. Summary and conclusions

The PDSI addresses two of the most elusive properties of droughts: their intensity and beginning and ending times. Unfortunately, the index uses rather arbitrary rules in quantifying these properties. In addition, the methodology used to normalize the values of the PDSI is based on very limited comparisons and is only weakly justified on a physical or statistical basis. Under certain conditions, the PDSI values are very sensitive to the criteria for ending an "established" drought. In addition, precipitation during a month can have a large effect on the PDSI values for several previous months. The conditional distribution of the PDSI given the value for the previous month may often be bimodal. Thus, conventional time series models may be quite limited in their ability to capture the stochastic properties of the index.

Published values of the PDSI are widely used, and there are likely many users who have a good engineering or intuitive judgment of their meaning. Considerable human judgment and experience, which are hard to quantify, went into development of the index. Until a "better" index is developed, the PDSI will likely continue to be used widely. This paper has documented several limitations of the method. However, more importantly, it should indicate a great need for additional research into drought indices while warning about some of the difficulties involved in their development.

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ESTIMATING WATER USE IN THE UNITED STATES

A New Paradigm for the National Water-Use Information Program

Committee on USGS Water Resources Research
Water Science and Technology Board
Division on Earth and Life Studies
National Research Council

National Academy Press
Washington, D.C.

6

Regression Models of Water Use

This chapter explores the structure of the past National Water-Use Information Program (NWUIP) state-level aggregated water use data, based on corresponding (and routinely collected) demographic, economic, and climatic data. The purpose of this inquiry is to determine if multiple regression models have the potential to explain the temporal and geographic variability across the United States of the aggregated water use estimates produced by the NWUIP. The statistical models examined here are derived using the U.S. Geological Survey (USGS) estimates of total withdrawals for public supply use and thermoelectric power use. A complete analysis of historical withdrawals is described in Dziegielewski (2002a).

NATIONAL WATER USE DATA

Total water use in the United States has been estimated by the USGS every five years since 1950. National estimates focus primarily on measuring total water withdrawals, which include the annual extractions of both fresh water (with separate estimates for surface water and groundwater withdrawals) and saline water. The total withdrawals are subdivided into categories; all point withdrawals are aggregated and reported at the county and state levels. The structure of these reported withdrawals in 1995 (Solley et al., 1998) can be represented as:

$$TW_t = \sum_i \left(PS_{it} + DM_{it} + CM_{it} + IR_{it} + LS_{it} + IN_{it} + MN_{it} + TE_{it}\right) \qquad (6.1)$$

where

TW_t = total (fresh and saline) water withdrawals in all states, the District of Columbia, Puerto Rico, and the U.S. Virgin Islands in million gallons per day (MGD) during calendar year t

PS_{it} = public supply withdrawals (in state i during year t) , MGD

DM_{it} = domestic (self-supplied) withdrawals, MGD

CM_{it} = commercial (self-supplied) withdrawals, MGD

IR_{it} = irrigation withdrawals, MGD

LS_{it} = livestock withdrawals, MGD

IN_{it} = industrial (self-supplied) withdrawals, MGD

MN_{it} = mining withdrawals, MGD

TE_{it} = thermoelectric withdrawals, MGD

In the 1995 compilation, freshwater withdrawals were estimated for all eight categories (or sectors), and saline water withdrawals were estimated for industrial, mining, and thermoelectric categories. The freshwater withdrawals are separated into groundwater and surface water for all sectors, and saline withdrawals are separated by source for industrial, mining, and thermoelectric sectors. For example, the total withdrawals for thermoelectric power use, TE_t , can be represented as:

$$TE_t = \sum_i \left(TE_{itfs} + TE_{itfg} + TE_{itbs} + TE_{itbg} \right) \tag{6.2}$$

where

TE_{it} = withdrawal for thermoelectric power use in state i during year t; and the subscripts f, b, s, and g respectively indicate freshwater, brackish or saline water, surface water, and groundwater.

These eight categories are nonoverlapping and sum up to total withdrawals. However, public supply withdrawals include water delivered by public water supply systems to some commercial, industrial, and thermoelectric uses, and detailed sectoral-use tables in Solley et al. (1998) show both the self-supplied withdrawals and deliveries of water to each sector.

The reported estimates are obtained primarily from detailed inventories of point withdrawals within each accounting unit (i.e., county or state). The point withdrawals represent measured volumes of water at pumping or diversion points or estimates of the withdrawn volumes based on the time of pump operation, irrigated acreage, or some other indirect measure. Indirect measures depend on water use category and assume a specific relationship between the quantities of water use and the values of the corresponding indirect measures (USGS, 2000, Chapter 11). Statistical models of water use permit an explicit consideration of the relationships between water use and these indirect measures. These relationships are discussed in the following section.

WATER USE RELATIONSHIPS

Water use at the state level can be estimated indirectly by using multiple regression analysis. In regression models, water use relationships are expressed in the form of mathematical equations, showing water use as a mathematical function of one or more independent (explanatory) variables. The mathematical form (e.g., linear, multiplicative, exponential) and the selection of the right-hand-side (RHS) or independent variables depend on the category and on aggregation of water demand represented by the left-hand-side (LHS) or dependent variable. A large number of econometric studies of water use have been conducted. Hanemann (1998) summarizes the theoretical underpinnings of water demand modeling and reviews a number of determinants of water demand in major economic sectors. Useful summaries of econometric studies of water demand can be found in Boland et al. (1984). Dziegielewski et al. (2002b) reviewed a number of studies of aggregated sectoral and regional demand. A substantial body of work on model structure and estimation methods was performed by the USGS (Helsel and Hirsch, 1992).

Depending on the purpose for which the estimates are used, the dependent variable (i.e., water use) can be presented in different ways. For example, in studies of surface and groundwater resources, the data are usually available as daily, monthly, or yearly withdrawals at a point such as a river intake or a well. Because the water withdrawn is typically used (or applied) over a larger land area, an equivalent hydrologic definition of water use would be the use of water over a defined geographical area (e.g., an urban area, a county, or a river basin). As shown in Equation 6.1, total water use within a larger geographical area such as a county or state can be presented as a sum of water use by several groups of users within a number of subareas.

Generally, water use at any level of aggregation can be modeled as a function of one or more explanatory variables. However, the best results are obtained by breaking down total water use by sector, because different subsets or explanatory variables apply to different sectors. For example, public supply withdrawals can be estimated using the following linear model:

$$PS_{it} = a + \sum_{j} b_j X_{itj} + \varepsilon_{it} \qquad (6.3)$$

where PS_{it} represents public supply withdrawals within geographical area i during year t, X_j is a set of j explanatory variables (e.g., air temperature, precipitation, price of water, median household income, and others), which are expected to explain public supply withdrawals, and ε_{it} is a random error term. The coefficients a and b_j can be estimated by fitting a multiple regression model to the historical data. This procedure has some parallels in modeling river loads, sediment-rating curves, and urban nonpoint pollution loads. Examples of studies of those subjects, which utilize statistical approaches, include Cohn et al. (1989) and Christensen et al. (2000).

WEATHER NORMALIZATION OF WATER USE

The quantity of water withdrawn in any given year depends on weather conditions. Water withdrawals for most purposes increase during periods of hot and dry weather and decrease during periods of cool and wet weather. This dependence of withdrawals on weather conditions can be determined by including weather-related variables in the set of explanatory variables X_j in Equation 6.3 above.

The accuracy of the weather adjustment depends on the length of the time interval used in data averaging. The best results are obtained by modeling time-series data on daily or weekly water use; the relationship can be masked when monthly and seasonal data are used. For example, water use is negatively correlated with precipitation. However, if monthly data are used, it is possible that total precipitation during a given month could be higher than normal but concentrated during the last two days of the month. Water use during that month would be higher than normal because of the dry conditions during all but the last two days of the month, thus indicating a misleading positive correlation between water use and precipitation.

The selection of variables to represent weather conditions depends on the sector. In models of domestic demands, commonly used measures of weather conditions include antecedent precipitation (or antecedent rainless days) and air temperature. Evapotranspiration is often used in models of water use for landscape watering and irrigation demands, and cooling degree-days and heating degree-days are used to estimate industrial demands or thermoelectric power use (Boland et al., 1984; Dziegielewski et al., 1996).

The use of weather variables in multiple regression models is illustrated in the later sections of this chapter. The next section explores the structure of water demand in public supply sector water use and presents several statistical models that were fitted to the historical estimates of public supply withdrawals in the lower 48 states.

STATE-LEVEL MODELS OF PUBLIC SUPPLY WITHDRAWALS

Public supply water is water withdrawn by public or private water suppliers and delivered to users. The public supply withdrawals estimated by the NWUIP for the years 1980, 1985, 1990 and 1995 in each of the lower 48 states were used in regression analysis. Twenty-one variables were selected as the likely predictors of public supply withdrawals at the state level and the following:

- *Population:* resident state population, population served, population density, and percent urban population;
- *Income:* median family income, state per capita income;
- *Economy/employment:* civilian labor force, gross state product per capita, average (weighted) price of water;
- *Housing mix:* percentages of single-family housing units, multifamily housing units, and mobile homes;
- *Weather:* total precipitation (during growing season), average air temperature (during growing season), and extreme monthly value of Palmer Drought Severity Index (PDSI); and
- *State water law:* prior appropriation, riparian or riparian with permits.

These variables are measures of demographics, affluence, economic activity, housing stock, weather, and water allocation arrangements. Six indicator (binary) variables were constructed to represent the legal systems of water rights in each state for allocating surface water and groundwater to uses and users. A measure of "dryness" for weather conditions was chosen as the lowest monthly value of the PDSI during the data year for each state. PDSI may have significant limitations in capturing the effects of dry weather on water use and has been found not to be a nationally consistent measure of dryness (Alley, 1984; Guttman et al., 1992). There are other indicators of the evaporative demand of the atmosphere as it affects the consumptive use of water (e.g., Class A pan evaporation, reference crop evapotranspiration); however, the availability of such measures at the geographical scales used in this analysis is limited.

Population served by public water supply systems was used to express the dependent variable as average public supply withdrawal per capita per day for each state and data year. If the per capita rate of withdrawal in each state can be predicted with sufficient accuracy, then total public supply withdrawals can be estimated by multiplying the per capita withdrawal by population served.

One advantage of modeling the per capita withdrawal is that by expressing total withdrawals in per capita terms, the dependent variable is "normalized" across states, and the problems associated with heterogeneity of total withdrawals among the states are avoided. Also, the "out of range" values of per capita withdrawal can be easily spotted in the data and investigated. It should be noted, however, that regression analysis can also be applied to total public supply, not just to per capita public supply withdrawals as described here.

It should be emphasized that the regression models presented here are for illustrative purposes only, as many details about model diagnostics and other aspects of the analysis have been omitted for clarity. Detailed discussions about potential bias in the estimators and alternative estimation techniques are described in Dziegielewski et al. (2002a).

Table 6.1 shows the coefficients of a linear regression (see Equation 6.3) of 1980–1995 state-level data (excluding the District of Columbia) on per capita public supply withdrawals using the ordinary least squares (OLS) procedure. The shorter data series for 1980–1995 was selected to take advantage of improved data collection procedures and to capture the recent trend of declining water use since the 1980 compilation.

The model shown in Table 6.1 explained 52 percent of the variance in per capita usage rates among states and across reporting years. The predictive properties (regression fit) of the model are limited as indicated by both the absolute and relative size of the residuals shown below the table. The mean absolute percentage error (APE) is 12.9 percent, and the root mean squared error is 31.6 gallons per capita per day (gpcd).

Despite the significant unexplained variance, the regression model in Table 6.1 can be considered to be a reasonable "explanatory" model, which reveals the structure of demand for public water supply even in the geographically aggregated data. The size and signs of the estimated regression coefficients fall within the ranges of expected values. These coefficients can be interpreted to mean that across the United States, from 1980 to 1995, the mean withdrawal was 183.7

TABLE 6.1 Linear Regression Model for State-Level Per-Capita Public Supply Withdrawals, 1980–1995

Dependent/Explanatory Variable	Regression Coefficient	t-Ratio	F-value Probability
Intercept (gpcd)	115.881	3.28	0.0012
Average price of water ($/1,000 gal., real 1995 dollars)	−7.779	−2.63	0.0091
Gross State Product per capita ($1,000, real 1995 dollars)	1.676	3.22	0.0015
Precipitation in summer months (May to Sept., in inches)	−2.119	−4.02	0.0001
Average temperature during summer (Fahrenheit degrees)	0.983	2.15	0.0326
Indicator of states with prior appropriation groundwater rights system	29.136	3.05	0.0027
Indicator of states with prior appropriation surface water rights system	17.218	1.81	0.0716

NOTES: Mean water use = 183.7 gpcd; n = 192; R^2 = 0.52; mean APE = 12.9%; root MSE = 31.6 gpcd; Nine observations of per capita withdrawal in the original data were adjusted using a data-smoothing procedure.

gpcd (from the data). This average withdrawal rate would decrease by 7.8 gpcd if price were increased by $1/1,000 gallons, and it would increase by 1.7 gpcd if the gross state product per capita increased by $1,000. Because a significant portion of public supply withdrawals is used to supply industrial and commercial uses, the gross state product variable captures the effects of the relative volume of nonresidential uses together with the effect of the ability to pay for water, which is typically captured by per capita or median household income variables in models of residential use. The binary indicator variable, which assumes the value of 1 for states with prior appropriation groundwater rights (generally western states), indicates that on average, these states withdrew 29 gpcd more than states with riparian and riparian with permits systems. Also, in states with prior appropriation surface water rights, average per capita withdrawals were on average higher by 17.2 gpcd than in riparian law states. The water rights variables most likely are an indirect measure of the arid climate of the states that use the prior appropriation system rather than indicating increased use because of appropriation rights.

The effects of individual explanatory variables can be also expressed in terms of elasticity of water demand with respect to changes in the values of each dependent variable. Elasticity measures the percentage of change in the independent variable that would be caused by a 1.0 percent increase in the value of independent variable. For example, the elasticity of demand with respect to price (estimated at the means) is –0.10. This value is found by multiplying the regression coefficient –7.779 by the ratio of average price to average per capita withdrawal in the data. An elasticity of –0.10 is relatively low (in absolute value), but it is close to expectation for aggregate public supply data. Also, the elasticity of demand with respect to income (as represented by gross state product) is +0.22. These elasticity values indicate that a 1.0 percent increase in price would result in a 0.10 percent decrease in demand while a 1.0 percent increase in per capita gross state product would result in a 0.22 percent increase in demand.

The estimated regression coefficients for temperature and precipitation in Table 6.1 clearly show the effect of weather on withdrawals and can be used in normalizing water use for weather. In this context, withdrawals during normal weather could be predicted by substituting into the regression equation "normal" values of average air temperature during summer months and total precipitation during the growing season for these dependent variables. The regression coefficients of the two weather variables in the model indicate that the average per capita demand in a state decreases by 2.1 gallons per day (gpd) per one-inch increase in precipitation during the growing season (elasticity at the mean is –0.19). The per capita demand increases by approximately 1 gpd per one-degree increase in average annual temperature (elasticity at the mean is +0.37). These elasticity values indicate that per capita public supply withdrawals decrease by 0.19 percent for each one percent increase in precipitation and increase by 0.37 percent for each one percent increase in average temperature.

The predictions from the model in Table 6.1 can be improved by supplementing them with information that is contained in model residuals (i.e., differences between actual and predicted values). This can be done by introducing binary variables, which designate individual states. In a model with binary state indicator variables, the average value of residuals for each state is added to the predicted value for that state thus reducing the prediction error. Similarly, if the state residuals contain an increasing or decreasing time trend, such a state-specific trend can also be added to the prediction. However, the addition of separate intercepts and time trends for some states does increase the number of model parameters. If the resulting model is overspecified, the coefficients of the continuous variables, which form the structural component of the model, may be biased. Such bias is small when the inclusion of a state-specific intercept (or trend) does not result in an appreciable change in the value of the estimated coefficients of the structural variables. Still, as with any statistical model, careful evaluation of the model predictions is recommended before accepting the final form of model.

An alternative model was fitted using a stepwise procedure that selected the best explanatory variables from both the continuous variables used in the model shown in Table 6.1 and the binary variables, which designate individual states. In addition, a time trend variable was fitted to the data with trend adjustments for several individual states. The model was estimated using a truncated subset of data for 1980, 1985, and 1990, which excluded the 1995 data. The estimated regression coefficients and other related information for this extended model are shown in Table 6.2.

An estimate of per capita public supply withdrawals for any state and year can be made using the model in Table 6.2. This can be done by substituting the corresponding values of price, per capita gross state product, total summer precipitation, and average temperature and adding four "intercept adjustors"—one for state groundwater law system, one for state surface water law system, one indicator of an individual state (if present in the model), and one state-specific trend (if present)—using the following equation:

$$PS_{it} = 90.659 - 4.726AP_{it} + 2.430GP_{it} - 1.299R_{it} + 0.777T_{it} + 17.356LG_{it} + 38.697LS_{it} + a_iS_i + b_iT_iD_i \quad (6.4)$$

where

PS_{it} = per capita withdrawal (gallons per day) in state i during year t
AP_{it} = average price in constant 1995 dollars
GP_{it} = gross state product per capita in constant 1995 dollars
R_{it} = total summer season precipitation in inches
T_{it} = average summer temperature, degrees Fahrenheit

TABLE 6.2 "Extended" Per Capita Model of Public Supply Withdrawals, 1980–1990

Variables	Estimate	Std Error	*t* Ratio	Prob>|*t*|
Intercept (gpcd)	90.659	23.195	3.91	0.0002
Average price of water ($/1,000 gal)	−4.726	1.624	−2.91	0.0044
Gross state product per capita ($1,000)	2.430	0.352	6.91	<0.0001
Total precipitation during summer, inches	−1.299	0.365	−3.55	0.0006
Average temperature during summer (deg. F)	0.777	0.270	2.88	0.0048
States w/ prior appropr. groundwater rights	17.386	7.529	2.31	0.0229
States w/ prior appropr. surface water rights	38.697	6.980	5.54	<0.0001
Indicator for Alabama	50.543	11.722	4.31	<0.0001
Indicator for California	−47.292	13.000	−3.64	0.0004
Indicator for Connecticut	−29.507	8.065	−3.66	0.0004
Indicator for Delaware	−25.258	7.956	−3.17	0.002
Indicator for Florida	16.950	8.513	1.99	0.0491
Indicator for Idaho	27.171	9.020	3.01	0.0032
Indicator for Kansas	−60.388	9.506	−6.35	<0.0001
Indicator for Massachusetts	−32.888	7.805	−4.21	<0.0001
Indicator for Michigan	16.514	7.894	2.09	0.0389
Indicator for Montana	36.237	8.938	4.05	<0.0001
Indicator for Nevada	80.910	8.395	9.64	<0.0001
Indicator for New Hampshire	−23.742	7.714	−3.08	0.0027
Indicator for New Jersey	−14.228	7.744	−1.84	0.069
Indicator for North Dakota	−104.913	12.410	−8.45	<0.0001
Indicator for Oklahoma	−56.023	12.707	−4.41	<0.0001
Indicator for Oregon	−26.390	8.667	−3.05	0.0029
Indicator for Pennsylvania	33.247	7.521	4.42	<0.0001
Indicator for Rhode Island	−27.130	7.639	−3.55	0.0006
Indicator for South Dakota	−70.827	9.011	−7.86	<0.0001
Indicator for Utah	64.321	8.721	7.38	<0.0001
Indicator for Virginia	−22.074	7.454	−2.96	0.0038
Indicator for Washington	32.040	12.270	2.61	0.0103
Indicator for Wisconsin	27.198	7.787	3.49	0.0007
Trend adjustor for Alabama	−3.333	1.769	−1.88	0.0622
Trend adjustor for California	3.555	1.765	2.01	0.0466
Trend adjustor for Illinois	2.645	1.201	2.2	0.0299
Trend adjustor for Maryland	4.453	1.144	3.89	0.0002
Trend adjustor for Nebraska	3.668	1.335	2.75	0.0071
Trend adjustor for North Dakota	3.960	1.754	2.26	0.0261
Trend adjustor for Oklahoma	4.724	1.758	2.69	0.0084
Trend adjustor for Texas	−3.853	1.313	−2.93	0.0041
Trend adjustor for Washington	−3.860	1.758	−2.2	0.0303

NOTES: $N = 144$; $R^2_{adj} = 0.93$; root MSE = 12.4 gpcd; mean APE = 6.3%.

LG_{it} = indicator for state groundwater law system (equals 1 if prior appropriation, 0 otherwise)

LS_{it} = indicator for state surface water law system (equals 1 if prior appropriation, 0 otherwise)

a_i = intercept adjustor for individual states

S_i = indicator for individual states (equals 1 if the state is included in the model, 0 otherwise)

b_i = trend coefficient describing changes in withdrawals in gpcd per year for individual states

Y_i = year since 1980 (equals 5 for 1985, 10 for 1990, and 15 for 1995)

D_i = indicator for state-specific trend (equals 1 gpd if the state is included in the model, 0 gpd otherwise)

This model in Table 6.2, which contains significant "intercept effects" for 23 individual states and trend effects for 9 states, explained 93 percent of variance in per capita withdrawals in the 1980–1990 data. The removal of one data year (1995) and the addition of binary variables had some effect on the estimated coefficients of the continuous variables when compared to those presented in Table 6.1. The coefficients of the price and precipitation variables have significantly less negative values when compared to the explanatory model in Table 6.1. The differences in the estimated coefficients indicate that the structural component of the model in Table 6.1 is not robust with respect to changes in the number of observations in the data and the inclusion of the binary variables to designate individual states. However, all six coefficients (including the binary water rights indicator variables) in Table 6.2 have the expected signs and remain statistically significant.

The model statistics shown below Table 6.2 indicate that the mean absolute percentage error (APE) for in-sample predictions is 6.3 percent as compared to 12.9 percent in the explanatory model (Table 6.1). The out-of-sample prediction errors for the 1995 data, which were not used to estimate the model, are shown for individual states in Table 6.3.

The comparison of the predicted and actual values in Table 6.3 indicates that the predictions for the 1995 data year were within ±10 percent for 24 states. In 17 states, the 1995 predictions were between ±10 percent and ±20 percent, and in 8 states, the absolute percentage error was greater than 20 percent. The largest error of 33.5 percent was obtained for California. The mean absolute percentage error for all 48 states in 1995 was 13.4 percent. The mean APE of 13.4 percent would also apply to the estimates of total public supply withdrawals for each of the lower 48 states (in million gallons per day), generated by multiplying the estimated per capita value by population served. If the model predictions for individual states were to be used to prepare an estimate of the total national public supply withdrawals for 1995, then due to the compensating positive and negative

TABLE 6.3 "Out-of-Sample" Predictions of Per Capita Public Supply Withdrawals for 1995

	Withdrawals (mgd)				Withdrawals (mgd)		
State	Actual	Predicted	% Diff.	State	Actual	Predicted	% Diff.
Alabama	237.1	171.4	−27.7	Nebraska	221.4	272.9	23.3
Arizona	206.1	231.5	12.3	Nevada	324.8	339.8	4.6
Arkansas	190.8	171.3	−10.2	New Hampshire	140.0	154.5	10.4
California	184.5	246.4	33.5	New Jersey	149.5	168.8	12.9
Colorado	207.7	238.5	14.8	New Mexico	225.4	239.7	6.3
Connecticut	155.2	164.0	5.7	New York	185.1	188.6	1.9
Delaware	158.6	169.9	7.1	North Carolina	162.1	170.1	4.9
Florida	169.1	172.0	1.7	North Dakota	148.9	176.9	18.7
Georgia	195.5	177.2	−9.3	Ohio	153.1	174.8	14.2
Idaho	242.9	256.7	5.7	Oklahoma	193.8	210.5	8.6
Illinois	175.3	217.7	24.2	Oregon	234.8	213.0	−9.3
Indiana	156.1	169.2	8.4	Pennsylvania	170.8	204.0	19.5
Iowa	173.2	171.1	−1.2	Rhode Island	130.2	147.1	13.0
Kansas	159.1	157.8	−0.8	South Carolina	199.6	158.8	−20.4
Kentucky	147.8	163.5	10.6	South Dakota	146.7	158.6	8.1
Louisiana	165.8	175.8	6.0	Tennessee	175.9	166.4	−5.4
Maine	141.7	160.5	13.3	Texas	187.7	169.0	−9.9
Maryland	200.0	244.7	22.3	Utah	268.9	304.2	13.1
Massachusetts	130.0	160.5	23.5	Vermont	148.3	164.2	10.7
Michigan	188.4	183.8	−2.4	Virginia	158.5	155.0	−2.2
Minnesota	145.2	178.0	22.6	Washington	266.3	216.0	−18.9
Mississippi	151.8	158.1	4.1	West Virginia	133.7	149.2	11.6
Missouri	161.5	167.9	4.0	Wisconsin	168.6	195.4	15.9
Montana	222.1	253.6	14.2	Wyoming	260.6	250.7	−3.8

prediction errors among individual states, the prediction error in the national total would be +2.2 percent.

STATE-LEVEL MODELS FOR THERMOELECTRIC WITHDRAWALS

State-level data for public water supply withdrawals are more accurate than data for thermoelectric cooling withdrawals. This is because public supply withdrawals are generally metered while withdrawals for thermoelectric cooling are more likely to be estimated based on pumping times and rated capacities of pumps.

The largest quantity of withdrawals from surface (and groundwater) sources is for thermoelectric power. The variables that can be examined as potential predictors of state-level thermoelectric withdrawals include the following:

• *Energy generation by fuel type:* total thermoelectric generation, percent coal generation, percent petroleum generation, percent natural gas generation, and percent nuclear generation;

• *Generation by method:* percent nuclear steam generation, percent conventional steam, and percent internal combustion;

• *Installed generation capacity:* total generation capacity (megawatt), percent conventional steam, percent nuclear steam, and percent internal combustion;

• *Availability of cooling towers:* total number of cooling towers, rated generation capacity with cooling towers (megawatt), number of cooling towers at coal steam plants, capacity (coal) with cooling towers (megawatt), number of cooling towers at petroleum/gas plants, capacity with cooling towers at petroleum/gas steam plants (megawatt);

• *Weather conditions:* cooling degree-days, heating degree-days, average annual air temperature;

• *State water law:* prior appropriation, riparian, riparian with permits; and

• *Number of generating units:* within coal, petroleum, gas, and nuclear categories.

Total withdrawals for thermoelectric power differ greatly among states, and the reported volumes are not well correlated with the total amount of thermoelectric generation in each state. However, when states with small generation and low water withdrawals (i.e., generally less than 1,000 MGD) are removed from the sample, a significant improvement in this relationship is achieved.

Table 6.4 presents a multivariate model of unit water withdrawals expressed as gallons per kilowatt hour for a group of states with large generation. The estimated regression coefficients indicate that the best explanatory variable for the quantity of withdrawals per kilowatt hour is percent generation capacity in plants that utilize "closed-loop" systems (i.e., cooling towers) relative to capacity

TABLE 6.4 Linear Model of Thermoelectric Withdrawals per Kilowatt-Hour

Variable	Estimated Withdrawal	*t* Ratio	Prob. >|*t*|
Intercept	49.376	15.53	<0.0001
Percent generation capacity with cooling towers	–0.362	–8.02	<0.0001
Percent utilization of existing capacity	–0.423	–4.99	<0.0001
Percent generation from coal	–0.096	–3.43	0.0009
Average size of generating units	0.174	6.34	<0.0001
Total heating degree-days	0.002	4.11	<0.0001
States w/ prior appropr. surface water law	3.962	–2.9	0.0047

NOTES: $N = 91$, $R2 = 0.80$; root MSE = 6.3 gal./kWh; mean APE = 17.6%.

of plants that depend on "once-through" cooling systems. Other predictors include percent utilization of existing capacity, percent thermoelectric generation from coal fuel, average size of generating units, and total heating degree-days. Additional explanation is provided by the "water law" variable, which indicates lower unit water withdrawals in states with prior appropriation surface water law (primarily western states). The model reveals the underlying structure of the thermoelectric demand despite the high level of data aggregation. All model coefficients have the expected signs and are statistically significant. They point to the importance of technological alternatives (i.e., once-through vs. evaporative cooling or combined-cycle generation) as determinants of water withdrawals.

Although the regression model in Table 6.4 explains 80 percent of the variance in per kilowatt-hour thermoelectric water withdrawals, the mean absolute percentage error for in-sample predictions remains relatively high at 17.6 percent. As in the public supply sector, improved predictions of the thermoelectric withdrawals model could be obtained by introducing binary state indicator variables.

Potential Model Improvements

The first step in improving the predictive properties of regression models of water use would be to enhance the quality of the data used in estimating the model parameters. Indeed, one of the advantages to regression approaches is that they may reveal cause-effect relationships that provide insight into data limitations. That is, because errors in the explanatory variables can be minimized, poor model predictions for individual states or years may suggest data errors in the USGS water use compilations. Thus, this approach may add value to both the assessment of water use and the quality control of the data. The effort expended to improve the data must, of course, be balanced with the effort expended to obtain reliable prediction variables.

Historical and current data on some of these explanatory variables exist, as they are routinely collected and archived by federal, state, and local governmental agencies. For example, the NWUIP currently collects data on population served and irrigated acreage. However, data on other variables, such as retail and wholesale water prices and thermoelectric generation capacity with cooling towers, are not routinely collected. If justified by their explanatory contribution in water use estimation models, such data collection and archiving could be added to NWUIP or state-level programs.

A second step would involve respecification of the predictive models. The relationships between the independent and dependent variables are likely to be different between the states of the humid East and the more arid West. The states, therefore, could be separated into groups based on geography and separate relationships estimated for groups of states, thus allowing the regression coefficients to vary among different regions of the country.

A third step would involve the introduction of additional variables in the multivariate regressions. Such variables, like marginal price of water or water conservation activity, are difficult to measure at the state level although they are known to have a significant influence on water use. For example, the results in Table 6.3 show a significant overprediction of per capita rates in California, a state with an aggressive water conservation programs. A variable that could capture the differences in water conservation efforts through time and among the different states could potentially improve these predictions.

Also, developing multiple regression models of withdrawals at the county level and obtaining the state totals by summing up the county-level estimates could also improve the state-level estimates of water withdrawals. However, the county-level data, which were developed by the NWUIP for 1985, 1990, and 1995, contain many apparent errors, and reliable models can be developed only after the accuracy of a number of data points can be verified.

Finally, given the potential for improvements in the data and models through the application of the "science of water use," the final statistical models for estimating water use may be of different form and structure than the examples developed here. However, the linear models used in this chapter to illustrate the approach do show the promise of the method.

CONCLUSIONS AND RECOMMENDATIONS

The examples presented in this chapter indicate that statistical models are a promising approach for estimating some categories of water withdrawals per unit (i.e., per capita or per kilowatt hour) within an acceptable estimation error. Based on the results presented in this chapter, the following conclusions can be drawn:

- A large number of potential explanatory variables for water use exist and can be used in constructing multiple regression models for the major categories of water withdrawals.
- Despite the state-level aggregation of the withdrawal data, these regression models reveal the underlying structure of water demand within several major sectors of use, and they reveal the key explanatory variables.
- The predictive properties of the models can be improved through appropriately specified models and through the inclusion of both the standard explanatory variables and the indicator variables for individual states or counties to capture their "unique" water use characteristics as well as state-specific trends in usage rates over time.
- The coefficients derived from regression models for adjustment of water use according to weather variations may be helpful in adjusting state-level water use estimates developed through statistical sampling or other means for departures from normal weather conditions in the year the estimates were made.

In summary, the data on water withdrawals and use that have accumulated under the NWUIP offer an excellent opportunity for advancing the "science of water use" and for understanding the structure and trends in national water use. The development of statistical models can be helpful in the quality assurance/ quality control process for future national compilations and for estimating water use in states or counties with inadequate data on withdrawals. Still, many challenges relating to data quality, inconsistent variable definitions, and statistical methodology need to be addressed, and they represent a fertile area for applied research as part of the NWUIP. *As part of its research on estimation methods, the USGS should undertake a systematic investigation of water use models as it has done for estimation of river loads, urban nonpoint pollution discharges, and other hydrologic quantities.*