TR-142
1987

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Technical Report No. 142

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This report is a joint effort between the Texas Water Resources Institute, Texas A&M University, and the Center for Research in Water Resources, The University of Texas at Austin. It is also published in identical form by CRWR as Technical Report CRWR 225.

August 1987

TEXAS WATER RESOURCES INSTITUTE
Texas A&M University
College Station, Texas 77843-2118

RESEARCH PROJECT COMPLETION REPORT

Project Numbers
G-1046-05
G-1254-05
(May 17, 1985 - August 31, 1986)
(September 1, 1986 - August 31, 1987)

Agreement Numbers
14-08-0001-G-1046
14-08-0001-G-1254

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The research on which this report is based was financed in part by the U.S. Department of the Interior, Geological Survey, through the Texas Water Resources Institute.

Technical Report No. 142
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Texas A&M University
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Technical Report CRWR 225
Center for Research in Water Resources
10100 Burnet Road
Austin, Texas 78758-4497

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ABSTRACT

In this research project, a methodology for automating the forecasting of municipal daily water use is developed and implemented in a microcomputer program called WATCAL. An automated forecast system is devised by modifying the previously-developed WATFORE model so that potential seasonal water use is calculated from a Fourier series fitted to seven-day weighted moving average values of daily maximum air temperature. A study is made comparing Kalman filtering and Box-Jenkins time series methods for automated model calibration. Although the Kalman filter method explains more of the time variation of the model parameters, the forecast accuracy of both methods is about the same. Box-Jenkins time series estimation algorithms specially designed for daily water use model parameter calibration, along with graphics and data editing routines, are implemented in WATCAL.

A study is also made of the impact of conservation programs implemented in Austin and Corpus Christi, Texas during the dry summers of 1984 and 1985. Mandatory conservation programs reduced water use in Austin about 10% and in Corpus Christi about 30% of peak summer usage. The effects of an undesirable five-day cycle in Austin's water use (caused by a mandatory watering scheme where addresses ending in a specified pair of digits were allowed to water on a given day) were analyzed. An alternative address digit pairing devised as part of this research eliminated the cycle during the summer of 1986.

A study of monthly and daily water use in five cities in Southern California shows that once water use data are made dimensionless, they follow a generic, weather-dependent pattern that is independent of city size and location within the region.

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1. OBJECTIVES AND SCOPE OF RESEARCH

1.1 Introduction. Municipal water utility managers need the ability to make short-term forecasts of water use, water use being defined as the combined pumpage of all water treatment plants in a city. Forecasts are needed in daily time intervals from a few days to a few months ahead, primarily during drought conditions when it is necessary to estimate the chance that extreme water use levels may occur. For example, the City of Austin, Texas has a water conservation ordinance requiring that mandatory restrictions on outdoor water use be implemented if total city water use exceeds a specified level for several consecutive days (Shaw and Maidment, 1986a). For municipalities relying on groundwater as a source of water supply, forecasts of pumpage may be necessary for assessing the probability that accumulated pumpage will lead to unacceptable drawdown in the aquifer. Additionally, it is desirable to have quantitative information concerning the effectiveness of conservation programs, both during conservation, and after the program has ended. Short-term water use forecasts are also important in scheduling water deliveries from distant supply sources such as upstream storage reservoirs. Furthermore, when preparing municipal budgets, it is usually necessary for water utility managers to forecast revenues for a subsequent fiscal period; this requires that an estimate of expected water use levels which might occur during the period be available.

This report is intended to provide an overview of a two year research project which continues a multi-year research effort at the

Center for Research in Water Resources, The University of Texas at Austin, on modeling and forecasting daily urban water use. This research effort began with the identification of climatic and socio-economic influences on the behavior of daily water use and has led to a structured, coherent model of the daily water use process called WATFORE.

The WATFORE model has been in use since 1984 in Austin, Texas for the purpose of predicting the onset of extreme water use levels which might adversely stress the distribution system or trigger the implementation of mandatory conservation restrictions. WATFORE is also used by the cities of Corpus Christi and Longview, Texas to assist in specifying upstream reservoir releases to meet city demand several days in advance. The forecast horizon in these cases corresponds to the flow time of the water from the reservoir to the city pump intakes. The City of Edmonton, Alberta, Canada uses WATFORE forecasts to assist in regulating storage within the city's water distribution system to avoid situations where low storage might stress the city's pumping. The WATFORE model has also been calibrated for use in San Antonio, Texas and San Diego, California, and is used for forecasting bulk water deliveries from long-distance water transfers by the Metropolitan Water District of Southern California. In addition to these cities, model coefficients have been determined for Philadelphia, Pittsburgh, and Allentown, Pennsylvania, Gainesville, Deerfield Beach, and Boca Raton, Florida, Dallas, and College Station, Texas, and Riverside, Las Virgenes, Burbank, and Fullerton, California.

The current research encompasses the theoretical development and microcomputer implementation of an automated model for purposes of short-term forecasting. The first year of this research project was devoted to developing a methodology whereby WATFORE could be tuned automatically to the most recent water use and weather data and adjusted for the time-varying characteristics of the system. Two different techniques, one an adaptive Kalman filter scheme, the other an automated Box-Jenkins time series estimation and forecasting methodology, were studied to determine their ability to provide high forecast accuracy in a time-varying environment. Much of this theoretical and methodological development was included in the Ph.D dissertation of Shaw-Pin Miaou (1986a) which was completed as part of this research project. A comparison of the two estimation/forecast techniques and an overview of their theoretical development as presented by Miaou are given in chapter 3 of this report.

The second year of the project encompassed the development of a microcomputer-based estimation/calibration package called WATCAL which can be used by those outside the research community, such as water utility managers or consultants. Implementation of this software package required that some additional changes be made in the methodology previously used for estimation; these changes are discussed in chapter 4 of this report. The resulting integrated daily water use modeling, calibration, and forecasting environment is comprised of two separate stand-alone packages: (1) WATCAL for estimation and calibration, and (2) WATFORE, the short-term forecasting program. Chapter 2 of this report gives a brief overview of the evolution of the WATFORE model since its conception, and discusses the development of the methodology used in the WATCAL estimation/calibration program. The final chapters of the report introduce two important applications and extensions of the water use modeling and estimation methodology. An application of the methodology to the estimation of impacts of conservation programs on daily water use in Austin and Corpus Christi, Texas is discussed in chapter 5. In chapter 6, a regional application of the WATFORE model to several different cities in Southern California is described.

1.2 Research Objectives. The objectives of this research project are as follows:

(1) To develop a self-calibrating version of the WATFORE forecasting model subject to the following constraints:

(a) the model can be fine-tuned by water utility managers, consultants, or others outside of the research community;

(b) the calibration scheme takes advantage of the most recent practically available data;

(c) the calibration scheme is adaptable to the time-varying character of the system being modeled;

(d) the combined calibration and forecasting methods provide high forecast accuracy;

(e) the combined calibration and forecasting methodology is automated and can be implemented on a microcomputer.

(2) To modify the WATFORE model and estimation methodology so that it is capable of evaluating the effectiveness of a water conservation program, both numerically and graphically. The methodology should:

(a) provide a numerical estimate of the magnitude of the impact of a conservation program and the standard error of the estimate;

(b) be able to reconstruct (given observed rainfall and temperature data) water use during the conservation period as if no conservation had taken place.

(3) To study the implementation of WATFORE on a regional basis to determine if the model can be reduced to a common form for cities within the geographic or climatic region so that generic sets of model coefficients can be used instead of treating each new city analyzed as a special case.

The research supported by this project was materially assisted by interaction with water utility personnel, principally the Cities of Austin, Corpus Christi and Longview, Texas; and the Metropolitan Water District of Southern California in Los Angeles, and its member agencies.

2. LITERATURE REVIEW - EVOLUTION OF THE WATFORE MODEL

An early and well-known residential water use study was carried out by Howe and Linaweaver (1967) using data from throughout the United States. Their study analyzed indoor use, average daily use, maximum daily use, and peak hourly use. One significant result of their study was that the difference between winter and summer indoor water use is insignificant in the locations they examined. Based on this result, later researchers (including Maidment, et al., 1985a) were able to assume that water use during the winter months consists only of indoor use, which is relatively unaffected by weather conditions, while summer use additionally includes outdoor use, which is sensitive to weather variations.

Many previous researchers have identified rainfall and air temperature as influential variables affecting the water use process on a daily or monthly scale, using multiple regression techniques (e.g., Anderson, Miller, and Washburn, 1980; Morgan and Smolen, 1976; Hansen and Narayanan, 1981; Steiner, 1984). Steiner (1984) and Anderson, Miller and Washburn (1980) further noted that rainfall had little effect on daily water use when rain amounts were less than a threshold level of about 0.1 inches. Additionally, the Anderson, Miller and Washburn (1980) study concluded that a lag-one-day relationship between rainfall and daily water use was significant.

Miaou (1983) investigated the dynamic relationship between rainfall and daily water use and found that water use is affected by the occurrence, rather than the amount, of rainfall (for rainfall above a threshold level of about 0.1 inches). Miaou developed a Box-Jenkins transfer function response model in which the decrease in water use on a rainy day is dependent upon the level of the previous day's outdoor water use. Miaou (1983) and Maidment, et. al. (1985a) show that this decreased water use due to rainfall persists for several days and then gradually returns to dry weather usage patterns. Maidment, et. al. (1985b) studied the effect of spatially-averaged rainfall from a number of gages in the Austin, Texas area and developed a more complicated relationship between spatially-averaged rainfall and the previous day's outdoor water use.

Miaou (1983) and Maidment, et. al. (1985a) introduced a model in which daily water use is made up of base and seasonal use components. Seasonal use itself consists of two components, one of which varies smoothly over the year with air temperature and another which represents the short-memory fluctuations:

$$W(t) = \hat{W}_b(t) + g(t)[\hat{W}_p(t) + W_s(t)] \qquad (2.1)$$

where t is a daily time index; W is daily water use; $\hat{W}_b$ is the estimated base (winter) use; g is a trend coefficient for peak seasonal use; W_p is estimated potential water use, a function of normal air temperature; and W_s is short-memory water use. Base use represents winter minimum water use (residential and commercial indoor water use plus any industrial use), while the seasonal water use reflects water used outdoors (primarily for lawn watering) during summer months. In general, both base and seasonal use components exhibit long-term trends through time. Maidment, et. al. (1985a) formulated a transfer function-noise model for the short-memory component:

$$W_s(t) = \overline{W}_s + \frac{\omega_{01}}{1-\delta_{11}B} T(t) + \frac{\omega_{02}-\omega_{12}B}{1-\delta_{12}B} R(t) + \frac{1}{1-\phi_1 B-\phi_2 B^2-\phi_7 B^7} a(t) \tag{2.2}$$

where W_s is the mean level component of short memory series; T is daily maximum air temperature; R is the previous day's seasonal water use level for rainfall days; a is a random shock (model error); ω, δ are transfer function coefficients; the ϕ's are autoregressive coefficients of the model errors; and B is the backshift operator, where $B[x(t)] = x(t-1)$.

This version of the model was implemented for use in short-term forecasting as a microcomputer program called WATFORE (Nvule and Maidment, 1985) and has been in use at the City of Austin, Texas and the Edwards Underground Water District in San Antonio, Texas since 1983 and 1984, respectively. In most of the early implementations of WATFORE, the original parameter estimation and any subsequent recalibration were performed at the University of Texas.

In their original model, Maidment, et. al. (1985a) defined the potential water use, W_p, to be a piecewise-linear function of normal daily maximum air temperature. The construction of this "heat function" was a tedious, manual procedure wherein subjective judgements were used to estimate the parameters of the function: (1) first, seasonal water use and climatic data were screened to eliminate data showing the effects of rainfall on the relationship between water use and air temperature; arbitrary criteria were used to define dry periods and thus screen the data, (2) seasonal water use and air temperature data were averaged over each seven-day dry period in the screened data set, (3) the selected data for weekly average values of seasonal water use were plotted against weekly average temperature so that break-points in the piecewise-linear function could be roughly estimated, (4) linear regression was applied to the screened, weekly-averaged data in an iterative manner by repeatedly choosing break-points and then estimating the slopes of the linear segments until a reasonable approximation of the heat function was obtained. The heat function, along with smoothed normal daily air temperature, was then used to calculate the potential seasonal water use. Obviously, this procedure was not well-suited to automation on a microcomputer and could not be performed by an inexperienced user without considerable study of the model and its behavior with many different data sets.

Regional variation of the model parameters was investigated by Maidment, et. al. (1985b) and Maidment and Miaou (1986) on daily water use data from three cities each in Texas, Florida, and Pennsylvania. One result of these studies was to remind the researchers of the weaknesses in the estimation procedure, especially the manual construction of the heat function. At that time, estimation and calibration were performed at the University of Texas using a combination of various microcomputer and mainframe data manipulation routines and a sophisticated time series modeling and estimation package on UT's CDC Cyber mainframe computer. This methodology made it difficult for an end-user (municipality or water district) to update or re-calibrate WATFORE without help from the researchers. One of the goals of this research was to simplify the WATFORE calibration procedure by eliminating manual data handling steps so that calibration could be done reliably by personnel outside the University of Texas.

3. THEORETICAL DEVELOPMENT

3.1 Modifications to the WATFORE Model.

3.1.1 De-seasonalization Scheme. Miaou (1986a) noted three other difficulties with the piecewise-linear heat function. First, it assumes that the water use-air temperature relationship follows a fixed pattern through time. Miaou (1986a) showed, using Fourier-smoothed weekly average water use and likewise smoothed weekly average (of daily maximum) air temperature, that there may actually be a hysteresis effect in the water use-air temperature relationship. That is, the slope of the water use - air temperature function may be steeper when temperatures generally are rising (in spring and early summer), and flatter when temperatures generally are falling (in late summer and fall). Miaou attributed this phenomenon to behavior persistency in water users, whereby high water use (most notably, lawn watering) tends to persist once it has begun. Also, lawn watering is related to evapotranspiration from the ground surface, and the time of peak evapotranspiration generally occurs earlier in the year than the time of peak air temperature. The second difficulty with the heat function method is that it is often difficult to obtain enough long-term data to adequately define the smoothed normal daily air temperature profile needed for calculating the potential use. Finally, the discontinuous nature of the piecewise-linear relationship is unrealistic since the actual behavior is continuously non-linear.

Miaou (1986a) suggested several different schemes for de-seasonalization and calculation of potential water use based on a three or four-harmonic Fourier series which tracks the annual variation in daily maximum temperatures:

$$W_p(t) = \{a_0+\sum_{j=1}^{NH}[a_j\cos(\eta jt)+b_j\sin(\eta jt)]\}T'(t) \qquad (3.1)$$

$$= f(t,T')$$

where

W_p = potential water use;

t = daily time index;

NH = number of harmonics used in model (4 in this study);

$\eta = 2\pi/365$;

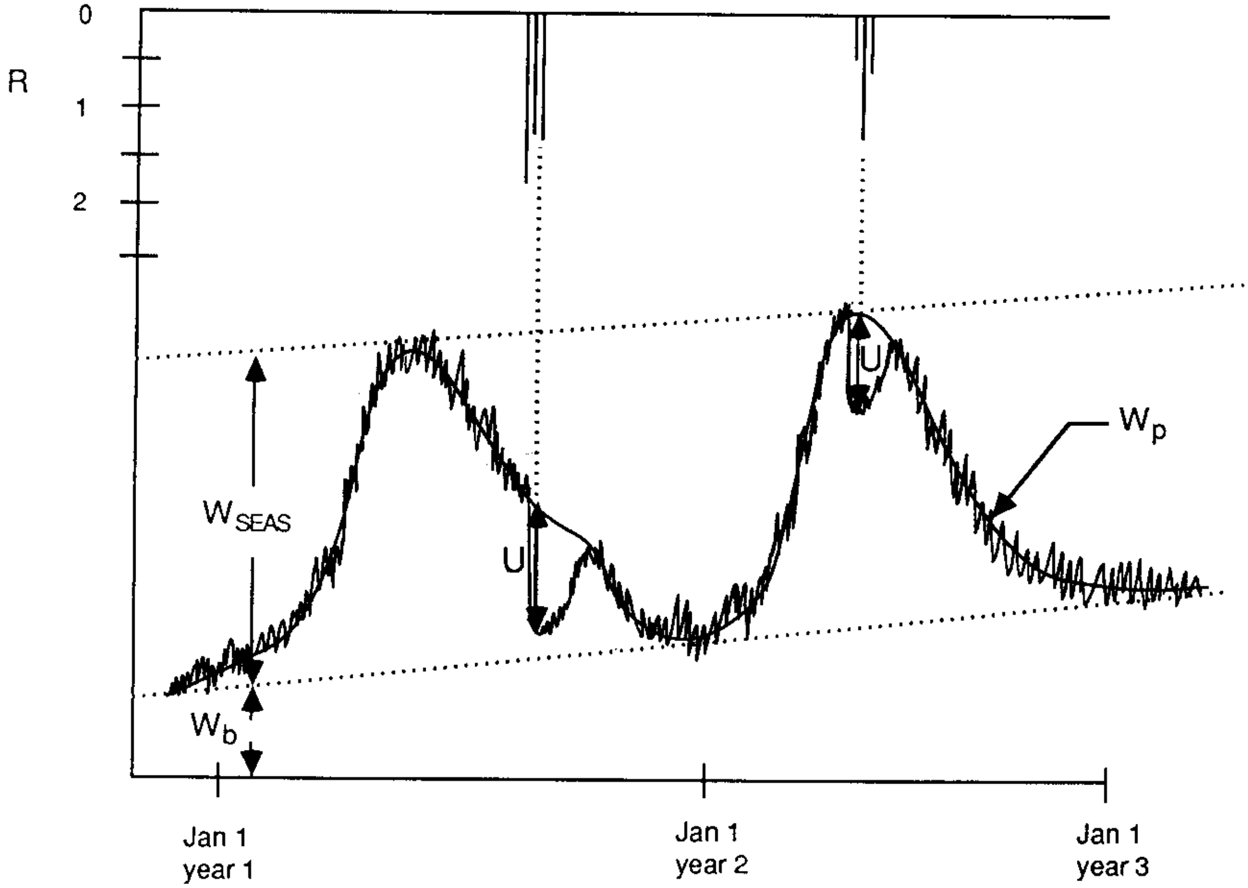
T' = a heating index equal to the average daily maximum temperature over the past seven days;

Such a formulation is much more amenable to automation than the previous method of estimating potential use via the heat function since the parameters of the Fourier series can be estimated along with the parameters of a rainfall impact function and other short-memory parameters, if necessary, using a non-linear optimization scheme. An additional advantage of this formulation is that hysteresis effects or other time variations in the water use-air temperature relationship will be captured by the Fourier series (Miaou, 1986a). Miaou (1986a) also proposed a generalized state-dependent potential use model in state-space form suitable for use with an extended Kalman filter estimation scheme. However, the ability of this model to adequately reconstruct potential water use, and its utility in operational forecasting were not assessed.

Miaou (1986a) investigated four variations of a de-seasonalization scheme based on the simultaneous estimation of the Fourier series coefficients of equation (3.1) and the parameters of a rainfall response function. Such a scheme is advantageous in that rainfall effects are automatically accounted for, and thus subjective manual screening of the data to remove those effects is not necessary. The major difference between the four methods is that methods (1) and (2) utilize observed seasonal use as the indicator variable to describe rainfall effects, while predicted seasonal use is used in methods (3) and (4). Methods (1) and (2) differ from each other only in the number of harmonics included in the Fourier series. Methods (3) and (4) are identical, except that a lag-one-day autoregressive parameter is added to the function in method (4) to account for bias in the estimation due to the tendency of water use on a given day to be highly correlated with water use on the previous day. The de-seasonalization schemes are put into equation form below; Figure (3.1) gives a schematic explanation of the variables in the equations. In the equations below, $\hat{W}_{seas}$ is the estimated seasonal water use (i.e., total daily water use less the base use), $W_p(t)$ is the value of potential water use given by the Fourier series model of equation (3.1), U(t) is the rainfall response function, and $L(t) = W_{seas}(t-1)$, yesterday's seasonal water use:

Figure 3.1

Definition Sketch, WATFORE Variables



$$U(t) = \frac{\omega_0{}^R - \omega_1{}^R B}{1 - \delta_1{}^R B} L(t)$$

The four schemes are:

$$\begin{aligned} &(1) \quad \hat{W}_{seas}(t) = W_p(t) + U(t), && j = 1, 2, 4 && (3.2) \\ &\qquad L(t) = W_{seas}(t-1), && R(t) > 0 && \\ &\qquad L(t) = 0, && R(t) = 0 && \end{aligned}$$

$$\begin{aligned} &(2) \quad \hat{W}_{seas}(t) = W_p(t) + U(t), && j = 1, 2, 3, 4 && (3.3) \\ &\qquad L(t) = W_{seas}(t-1), && R(t) > 0 && \\ &\qquad L(t) = 0, && R(t) = 0 && \\ &(3) \quad \hat{W}_{seas}(t) = W_p(t) + U(t), && j = 1, 2, 3, 4 && (3.4) \\ &\qquad L(t) = \hat{W}_{seas}(t-1), && R(t) > 0 && \\ &\qquad L(t) = 0, && R(t) = 0 && \\ &(4) \quad \hat{W}_{seas}(t) = W_p(t) + U(t) + N(t), && j = 1, 2, 3, 4 && (3.5) \\ &\qquad L(t) = \hat{W}_{seas}(t-1), && R(t) > 0 && \\ &\qquad L(t) = 0, && R(t) = 0 && \end{aligned}$$

in which the lag-one autoregressive error model, N(t), is defined as

$$N(t) = \frac{1}{1 - \phi_1 B} a(t)$$

Using 1980-1982 daily water use, rainfall, and temperature data from Austin, Texas, parameters were estimated for each of the four Fourier series-based de-seasonalization schemes. For each case, the estimation procedure was to first remove long-term trends in base and seasonal use from observed water use data using the procedures outlined in Maidment, et. al. (1985a), then to estimate the parameters of each of equations (3.2) through (3.5) such that the sum of the squared differences between modeled and observed seasonal use was minimized. The iterative Marquardt algorithm was used for this non-linear least-squares estimation exercise. After the Fourier series, rainfall response function, and noise parameters (if any) are estimated, the resulting potential water use models were used to reconstruct potential water use for each year in the data set, and were compared with observed seasonal water use for that year.

Table (3.1) gives the residual mean and variance after each de-seasonalizing procedure is performed. In the table, case (0) refers to de-seasonalization using the piecewise-linear heat function, and is provided for comparison. Referring to Table (3.1), it is clear that all four forms of Fourier series-based de-seasonalization outperformed the piecewise-linear heat function in terms of the residual variance (a lower residual variance indicates that a higher percentage of the original signal was extracted by the de-seasonalization scheme). It is also clear from the variances listed in the table that methods (3) and (4) outperformed methods (1) and (2). In the real-time forecasting process, the observed seasonal use is not available (except for the first day of the forecast), and hence the predicted seasonal use must be substituted. Therefore, for cases (1) and (2), a long-term forecast (i.e., beyond one day ahead), the forecast values are not optimal in the sense of least squares because the parameters of the model were estimated using observed seasonal use. An obvious question at this point is: if predicted seasonal use must be substituted for observed

TABLE 3.1 - Residual Mean and Variance After De-seasonalization

Deseasonalization Scheme	Mean	Variance
0	-0.218	216.1
1	0.580	144.4
2	-0.036	136.9
3	-0.520	70.4
4	-1.245	81.7

(0): piecewise-linear heat function with manual screening to reduce rainfall effects

(1): Fourier series model of potential water use (with harmonics 1, 2, and 4) and yesterday's observed seasonal use as an indicator of rainfall (Equation 3.2)

(2): same as (1), except the Fourier series model of potential water use includes harmonics 1, 2, 3, and 4 (Equation 3.3)

(3): same as (2), except yesterday's predicted seasonal use is used as the rainfall indicator (Equation 3.4)

(4): same as (3), with the autoregressive noise component, N(t), included to reduce estimation bias (Equation 3.5) seasonal use in methods (1) and (2), then why not estimate the parameters using predicted seasonal use in the first place? Indeed, this is what is done in methods (3) and (4); accordingly, these deseasonalization schemes can be considered optimal for any forecast horizon. Miaou (1986a) notes that methods (1) and (2) may be of some use for short-term forecasting, since forecasts made using these methods are optimal in the short term, and used observed, rather than predicted values. Reconstructions of 1980-1982 Austin, Texas data using methods (1) and (2) produced potential use curves which fell below observed seasonal use for those years. This violates the original assumptions of the water use model, where potential use is defined to be a function of recent heat condtions, free from rainfall effects.

The motivation for including the first-order autoregressive parameter in method (4) came from an examination of the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals of method (3). Miaou (1986a) notes that the ACF and PACF of method (3) residuals exhibit the characteristic AR(1) pattern described by Box and Jenkins (1976), thus indicating that the residuals were not a white noise series, and, accordingly, that forecasts made using this method would not be optimal in the least-squares sense. Although, in Table (3.1), the residual variance for method (3) is slightly lower than for method (4), Miaou suggests the use of method (4) in operational forecasting because of the fact that parameter values so obtained (i.e., with the inclusion of ϕ_1 in the equation) were more realistic. However, Miaou also noted that, on some occasions, the ϕ_1 parameter in method (4) tended to be significantly larger than the lag-one autocorrelation, r_1, from method (3). Following the logic of Box and Jenkins (1976), the lag-one autocorrelation from method (3) should be nearly equal to the ϕ_1 parameter in method (4); indeed, Box and Jenkins suggest using r_1 as an initial estimate for ϕ_1. The fact that $\phi_1 > r_1$ suggests that some of the rainfall effect was being modeled as noise in method (4). Reconstructed potential use was in most cases greater than observed seasonal use when using methods (3) and (4) for de-seasonalization. The de-seasonalization scheme (4) is used in the WATCAL estimation/calibration package which will be described in chapter 4. In a subsequent study, Shaw (1986) compared performance of the Fourier series model of potential water use (method 4) with piecewise-linear and quadratic heat function models whose parameters were estimated simultaneously with the short memory parameters and found the Fourier series model superior in reconstructing historical water use in Austin and Corpus Christi, Texas.

3.1.2 Weekly Cycle. A recent change in the model based on the results of calibrating WATFORE to water use data from five cities in southern California involved replacing the seven-day lag autoregressive parameter in the noise model (ϕ_7 in equation 2.2) with an intervention transfer function of the form:

$$WC(t) = (\omega_0 + \omega_1 B + \omega_2 B^2 + \omega_3 B^3 + \omega_4 B^4 + \omega_5 B^5 + \omega_6 B^6)\ IW(t) \tag{3.6}$$

where WC = the weekly cycle component of short-memory daily water use; IW = 1 on Mondays, and 0 on all other days of the week. This function was found to model water use data showing strong weekly cycles better than the single parameter ϕ_7. The function can also be used to account for differences in weekday and weekend water use patterns and also for lawn watering cycles due to odd/even or other such rules imposed during mandatory water conservation programs (for an example, see chapter 5). In his study of water use in Southern California, Miaou (1987) employed a Fourier series to represent the weekly cycle; however, the parameters of the intervention type model of equation (3.6) were judged to be more physically meaningful than Fourier series coefficients. A state-space formulation of equation (3.6) was also proposed by Miaou (1986a).

The changes described in this chapter have been incorporated into the present version of WATFORE and into the estimation strategy (to be described in chapter 4). The overall water use model is still described by equation (2.1). W_p, now defined to be the seasonal water use, is modeled using equation (3.5), and short-memory water use is modeled using the weekly cycle function, WC, given by equation (3.6), instead of the seven-day autoregressive function used in equation (2.2):

$$W_s(t) = \mu + \frac{\omega_0{}^T}{1-\delta_1{}^T B} T^*(t) + WC(t) + \frac{1}{1-\phi_1 B-\phi_2 B^2} a(t) \qquad (3.7)$$

where the transformed air temperature, $T^*(t) = f(t,T-T')$; and f is the Fourier series function defined in equation (3.1). Note also that the rainfall response function is included as part of W_p (equation 3.5), instead of W_s, and therefore is not included in equation (3.7) above.

3.2 Adaptive Estimation Using Kalman Filtering.

3.2.1 Application of the Kalman Filter Algorithm. During the past two decades, adaptive forecasting models, many of them employing Kalman filtering schemes, have been developed in fields such as streamflow forecasting, rainfall-runoff prediction, precipitation prediction, electric power load forecasting, and hourly urban water demand forecasting for purposes of short-term control (see Miaou, 1986a, for a review). The Kalman filter (Kalman, 1960) is a statistically-based algorithm for recursively estimating unknown, time-varying, parameters of a model of a dynamical system (in state-space form). Using this algorithm, the estimate of the unknown values of the state (including the unknown model parameters) can be updated each time a new observation is obtained. The updating is performed by weighting the state estimate according to the relative influence of the variance of the observations and of the variance of the previous state estimate. The next forecast is made using the updated state as the point of departure. If the variance of the observations is small relative to the variance of the state, then the forecast will be influenced more by recent observations; conversely, if the variance of the previous state estimate is smaller than the variance of the observations, then the forecast will be influenced mostly by the historical data. Miaou (1986a) presents the basic equations of the method in state-space form and gives a detailed outline of a sequential Kalman filter algorithm which can be used in a real-time daily water use forecasting environment.

Using heuristic methods, the Kalman filter may be tuned to make it more or less sensitive to incoming data; thus adjustments can be made to account for outliers in the data. In short-term forecasting of daily water use, it is usually assumed that no rainfall will occur during the forecast period (this is due to the general lack of knowledge of the rainfall point process, and also the fact that water use is decreased during rainy periods, so assuming dry conditions will prevail gives a safer, more conservative forecast). Thus, when rainfall does occur and the water use decreases (in the summer this decrease can be quite dramatic), large prediction errors will occur. This, in turn, leads to overcompensation by the updating mechanism of the Kalman filter and is a critical problem in the applications of Kalman filtering to water use forecasting. In order to avoid overcompensation, Miaou (1986a) added a screening mechanism to the algorithm which allows updating of the parameters only on dry days for which the day before was also dry. The noise model parameters also help to tune the forecast during a rainy period (Miaou, 1986a). Additionally, if an outlier (defined to be an observed data value which produces a forecast error greater than twice its estimated standard error) is detected, then no updating is allowed.

In practical applications of the Kalman filter, the variance-covariance structure of the state and of the observations, which influences both the estimated one-step ahead state covariance and the estimated one-step ahead forecast covariance, is generally not known and must be estimated. Many methods have been proposed to estimate these quantities, ranging from theoretically-derived approaches to empirical guesses and heuristics. When these covariances are estimated recursively from the data, the resultant algorithm is called an adaptive Kalman filter. The most robust method for estimating these covariances, maximum likelihood estimation (see Mehra, 1972, for theoretical derivation), was employed by Miaou (1986a) in his study. The maximum likelihood method takes advantage of the fact that one-step ahead forecast errors of the Kalman filter algorithm are independently and normally distributed random variables (this is known as the white noise, or innovations, property of the forecast errors; see Harvey, 1981, for a proof) such that a function of the unknown covariances can be constructed from the joint distribution of the forecast errors. In order that the forecast errors of his model exhibit the innovations property, Miaou (1986a) devised the following likelihood function which is dependent not only on the unknown covariances, but also on the unknown parameters of the short-memory water use model.

$$L = \prod_{t=1}^{ND} (2\pi \hat{C}_t)^{-1/2} \exp\{-\nu_t^2/(2\hat{C}_t)\} \tag{3.8}$$

where ND = number of days in the estimation data set;

$\hat{C}_t$ = one-step-ahead forecast variance from the Kalman filter algorithm;

ν_t = one-step-ahead forecast error from the Kalman filter algorithm.

The likelihood function given by equation (3.8), or its concentrated form (obtained by taking the logarithm of equation (3.8) and eliminating constant terms), may be maximized using a numerical optimization routine. This set of values is then used in the Kalman filter algorithm for recursive forecasting and updating.

3.2.2 Forecasting Experiments. The main reason for employing a Kalman filter to the estimation and forecasting of daily water use is that the filter is able to track model parameters which vary through time, and to correct the forecasts accordingly. Miaou (1986a) employs a state-space random walk model for time-varying short-memory parameters. Miaou determined the relative variability of each parameter in the short-memory model of equation (3.7) by allowing the mean, μ, to vary in a random walk fashion, and then including each of the parameters in the state vector and estimating their variances using the maximum likelihood method discussed in the previous section. The series of short-memory water use was obtained by using equation (3.4) to de-seasonalize 1980-1982 data from Austin, Texas. Of the four parameters in the short-memory model (equation 3.4), only two had large enough variances to be considered time-varying: the short-memory mean, μ, and the immediate (lag-zero) short-memory temperature effects parameter, ω_0^T.

Miaou tested six different short-memory water use models with various de-seasonalization schemes and various combinations of time-varying and constant parameters:

(1) Original WATFORE model of Maidment, et. al. (1985a) with constant parameter transfer functions, using the piecewise-linear heat function for de-seasonalization;

(2) Same as (1) with immediate short-memory temperature effects parameter, ω_0^T, varying in time by Kalman filter;

(3) Original WATFORE transfer functions (with no rainfall component included; equation 3.7), using Fourier series de-seasonalization method (3), (equation 3.4);

(4) Same as (3) with ω_0^T varying in time by Kalman filter;

(5) Same as (3) with the short-memory mean, μ, varying in time by

Kalman filter;

(6) Same as (3) with both ω_0^T and μ varying in time by Kalman filter.

For the forecast experiments, parameters were estimated using 1980-1982 water use, rainfall, and temperature data from Austin, Texas. Forecasts were made each day from 1982 through the summer of 1984 (the summer of 1982 was relatively hot and dry, the summer of 1983 was wet, with regular rainfall throughout, and the summer of 1984 was again hot and dry, with water conservation measures being implemented from May through September) for lead times of one, three, seven, ten, fourteen, seventeen, and twenty-one days. The forecasts were then compared to observed 1982-1984 water use in Austin, Texas, and were evaluated using three performance criteria: (1) mean absolute percentage forecast error, (2) mean absolute forecast error, and (3) mean squared forecast error (Miaou, 1986a).

The results of these experiments can be summarized as follows:

(i) In the dry summer months of 1982, time-varying parameter models had better forecast performance than constant parameter models for short lead times from one day to about ten days. Conversely, the constant parameter models performed as well, or better, than the time-varying parameter models for longer lead times from two weeks to three weeks. This indicates that the time-varying parameter model used more localized information than the constant parameter model.

(ii) During the summer months of 1983, which were unusually wet, the group of models using the piecewise-linear heat function deseasonalization scheme consistently outperformed the models using the Fourier series method for all lead times. This may indicate that estimating rainfall effects with the short-memory water use model, as is done when using the heat function scheme, is more appropriate than estimating rainfall effects in the de-seasonalization stage (as when using the Fourier series method) for forecasting during wet summer years. An alternative explanation is that Fourier series fits the characteristics of observed data: water use in Austin from 1980-82 was higher than in 1983, so the fitted Fourier series tended to overestimate usage in 1983.

(iii) During the dry summer months of 1984, the group of models using the Fourier series method consistently outperformed another group of models using the heat function. This implies that if the model will be used to forecast conditions far into the future (e.g., forecasting 1984 water use based on parameters estimated from 1980-1982 data, as in this case), then the Fourier series method is a better scheme than the heat function method provided the weather conditions are similar in the forecast period to those in the calibration period.

(iv) The model with a time-varying mean level performed better than the model with a time-varying temperature parameter in dry summers, but worse in the wet summer. This is because rainfall during the wet summer months continually interrupted the water use mean level and made it difficult to estimate.

(v) By comparing the mean absolute percentage forecast errors, the model with the time-varying temperature parameter was found to perform better in the dry summers than in the wet summer. One indication of this result was that temperature is not as good an indicator of water use in wet years as it is during dry years.

While the comparisons above shed further light on the scientific foundations of forecasting daily water use, the results do not conclusively prove the merits of using the Kalman filter method of estimation and updating in an operational forecasting system. Although the time-varying models were shown to explain more of the parameter variation through the year, their forecast accuracy was not significantly different from that of the constant parameter models. In light of this fact and, additionally, the fact that the Kalman filter algorithm requires some amount of manual tuning in order to perform correctly, the following recommendations were made for implementing a self-calibrating forecasting software package:

(1) The Fourier series de-seasonalization scheme should be used instead of the piecewise-linear heat function since the Fourier series method is much more amenable to automation and explains more of the total variance in the water use data (86.3% vs. 64.5%, respectively, for 1980-1982 Austin data).

(2) Fourier series method (4) (equation 3.5) is recommended since it outperforms the other Fourier series models and gives more realistic parameter estimates.

(3) The constant-parameter short-memory model of equation (3.7) estimated by standard time series methods should be used rather than a time-varying model which employs a Kalman filter. The Box-Jenkins time series estimation techniques are, at the present, more robust, and are easier to implement (especially on a microcomputer) than is the Kalman filter algorithm. However, an implemented forecasting system must have the capability to re-calibrate (i.e., re-estimate) model parameters whenever it is deemed necessary by the user.

Implementation of this recommended estimation and forecast system is described in the next chapter.

4. CODE DEVELOPMENT AND IMPLEMENTATION

4.1 Parameter Estimation. The use of non-linear optimization routines such as the Marquardt algorithm (Marquardt, 1963) was suggested by Box and Jenkins (1976) for numerical estimation of time series model parameters; this scheme was employed in the water use modeling methodology of Miaou (1983) and Maidment, et. al. (1985a,b). Miaou (1986a) also investigated the use of Kalman filter techniques for on-line, real-time estimation and updating of selected model parameters, but found that there was little improvement in forecast accuracy gained by using such a procedure as compared with using off-line estimation (see section 3.2).

One of the main drawbacks of the practical implementation of many numerical estimation techniques is the problem of providing good initial estimates. While methods such as Marquardt's algorithm are extremely powerful in that estimation of parameters of non-linear models is possible, they require initial guesses of the parameter values and are very sensitive to changes in these initial estimates. In some cases, such as satellite orbit determination problems, the correct parameter values are known to a fair degree of accuracy in advance since much of the variation in an orbit can be explained using deterministic theory. In many other practical situations, especially in those emerging fields such as the analysis of daily water use, which lack the substantial research base of fields such as orbital mechanics, this is not the case.

Some attempts to overcome this problem have been suggested. The use of automatic parameter identification techniques has been investigated (S.-P. Miaou, personal communication) for determining initial estimates of parameters based on the statistical correlation properties of the daily water use time series. However, these methods were judged to be too cumbersome for microcomputer implementation and too complicated for use by those outside the research community.

In order to meet the research goal of providing an automated, microcomputer-based software package, it is required that a procedure for determining initial estimates be quick to execute and give consistent, physically reasonable results. Since the largest portion of the total annual variation in daily water use is explained by the Fourier series model of seasonal use, and since nine out of twenty-eight total estimated parameters are contained in the Fourier series, it was decided to concentrate efforts on getting good initial estimates of these parameters first.

The cascade method of estimation, which will be explained in the next section, makes it possible to treat each source of variation in the overall model separately and then remove its effects from the water use series. Thus the parameters of the Fourier series seasonal use function are estimated first; initial estimates are determined using a discrete Fourier transform procedure which will be described in section 4.1.3. Numerical estimation of the remaining parameters in the model can be performed using the residuals of the previous step(s). Since these additional sources of variation are not as influential as the seasonal variation described by the Fourier series, determination of the initial estimates is not as crucial. Moreover, the use of dimensionless water use in the estimation algorithms (see section

4.1.2) simplifies choosing initial estimates of even these short-memory model parameters to the point where a generic set of initial estimates can be used within any geographic or climatic region.

4.1.1 Cascade Method of Estimation. The general estimation methodology employed by WATCAL for daily water use data is analogous to the cascade method of modeling and estimation used by Maidment and Parzen (1984a,b) on monthly water use for six Texas cities. Each source of variation is modeled separately and then removed, leaving a series of residuals for use in estimating the remaining parameters. Using the cascade method, the longer time-scale variations (long-term year-to-year trends in base and peak seasonal water use) are estimated first, followed by variations within a year (seasonal water use as a function of the annual temperature variation and rainfall), and finally short-term variations due to temperature fluctuations above or below normal, weekly patterns, and short-term memory effects.

In WATCAL, the long-term trends are modeled as linear trends in monthly water use data with corrections for average monthly temperature and rainfall (see Miaou, 1983 or Maidment, et. al., 1985a for details). The parameters are estimated using Marquardt's algorithm (Marquardt, 1963) and these trends are then removed from the daily water use series (as is described in section 4.1.2) after converting the parameters from a monthly to a daily scale. Initial estimates of the parameters of the Fourier series model of seasonal water use are calculated via discrete Fourier transform of the residuals. These initial estimates are used in the numerical estimation, again using Marquardt's algorithm, of the seasonal water use model (equation 3.5) consisting of the Fourier series, a transfer function which accounts for rainfall effects, and an autoregressive component which accounts for lag-one memory effects. The residuals at this stage are then fit to Box-Jenkins transfer functions which account for short-term temperature effects, weekly patterns, and process noise; these short-memory parameters are also estimated using Marquardt's algorithm. As a last step, the variance of the final residuals is computed; this quantity is equivalent to the one-day-ahead forecast error (see Box and Jenkins, 1976, for proof) and is used by the WATFORE program for calculating probabilities of exceeding specified water use levels during the forecast period.

4.1.2 Use of Dimensionless Water Use. It was shown in Maidment, et. al. (1985b) and Maidment and Miaou (1986) that daily water use could be made dimensionless by subtracting the base and dividing by the peak seasonal water use:

$$W_D(t) = [W(t) - W_b(t)] / S(t) \tag{4.1}$$

where W_D is dimensionless daily water use, and W_b and S are, respectively, the estimated base (minimum monthly use) and estimated peak seasonal water use (difference between minimum and maximum monthly use). The base use is estimated by fitting a linear regression trend through January or February (the minimum water use months in Texas) monthly water use data, and converting the resulting equation to a daily time scale. Peak seasonal use is estimated by subtracting the estimated monthly base use from the total monthly use during maximum water use months (usually July or August in Texas) and then fitting a regression line corrected for monthly average temperature and rainfall.

Maidment, et. al. (1985b), Maidment and Miaou (1986), and Miaou

(1987) demonstrate that the dimensionless daily water use for different cities in a given climatic/geographical region is quite similar. Thus, making the water use series dimensionless reduces data from each city to a common basis, enabling cities of different size and location to be compared and also providing a frame of reference from which to judge the validity of the final estimates. As a result of using dimensionless quantities, reasonable initial estimates of the short-memory parameters for a given data set can be chosen from the published or tabulated results of previous calibrations of the model to water use series from the same general geographic or climatic region. A more detailed study of the regionalization of the WATFORE model will be summarized in chapter 6. Indeed, initial estimates of short-memory parameters are now commonly chosen to be typical or average values determined from previous calibrations performed at the University of Texas at Austin. Currently, the model has been calibrated to water use in the cities of Austin, Corpus Christi, Longview, Dallas, College Station, and San Antonio in Texas, the cities of Deerfield Beach, Boca Raton, and Gainesville in Florida, the City of Edmonton, Alberta, Canada, the cities of Pittsburgh, Allentown, and Philadelphia in Pennsylvania, the cities of San Diego, Riverside, Las Virgenes, Burbank, and Fullerton in California, and the Metropolitan Water District of Southern California.

4.1.3 Estimation of Fourier Series Parameters. A good initial estimate of the seasonal variation of water use can be obtained using the classical discrete Fourier transform (DFT) of detrended (dimensionless) water use divided by the seven-day average air temperature (as used in equation 3.1). The logic of this method is that by dividing $W_p(t)$ by $T'(t)$ in equation (3.1), the result is a pure function of the time (calendar day of the year) which can be fitted by the DFT. However, at this estimation stage, the potential water use, W_p, has not yet been determined numerically, and W_D, the detrended (dimensionless) water use, is substituted. Since W_d includes short-memory effects as well as the seasonal variation, the resulting DFT-estimated parameter values can only be interpreted as approximate estimates of the coefficients of equation (3.1), and will be used as initial estimates to the full seasonal use model of equation (3.5). Using the DFT, the least-squares estimates of parameters of a three or four-harmonic Fourier series are obtained from the following equations (see, for example, Kottegoda, 1980 for details of the derivation):

$$\alpha_i = (2/ND)\sum_{t=1}^{ND} X(t)\cos(2\pi it/p), \qquad i = 1, 2, 3, 4$$

$$\beta_i = (2/ND)\sum_{t=1}^{ND} X(t)\sin(2\pi it/p), \qquad i = 1, 2, 3, 4 \qquad (4.2)$$

$$\alpha_0 = (1/ND)\sum_{t=1}^{ND} X(t)$$

where $X(t) = W_D(t)/T'(t)$, $p = 365$ (or 366 for leap years) for an annual periodicity, and ND is the total number of daily data available for estimation. The parameters α_i and β_i (i=0,1,2,3,4) obtained from equations (4.2) may then be used as initial estimates to a more accurate estimation of the seasonal water use function. Final estimates are obtained by using the Marquardt algorithm to fit parameters to the following function (same as equation 3.5):

$$W_{seas}(t) = \{a_0 + \sum_{j=1}^{NH}[a_j\cos(\eta jt) + b_j\sin(\eta jt)]\}\ T'(t) + U(t) + N(t) \tag{4.3}$$

where $$U(t) = \frac{\omega_0{}^R - \omega_1{}^R B}{1 - \delta_1{}^R B} L(t)$$

$$L(t) = \hat{W}_{seas}(t-1), \qquad R(t) > 0$$

$$L(t) = 0, \qquad R(t) = 0$$

$$N(t) = \frac{1}{1 - \phi_1 B} a(t)$$

Discussion of the theoretical development of this function was given in Chapter 3. The short-memory variations can then be interpreted, in terms of the cascade methodology, as deviations from the curve defined by equation (4.3). The lag-one autoregressive parameter, ϕ_1, in equation (4.3) is itself used as the initial estimate for the AR(1) parameter (also called ϕ_1) in the more complicated noise model of equation (3.7). Further explanation of the physical interpretation of the short-memory parameters is given in Maidment, et. al. (1985a).

4.2 Implementation of WATCAL

The program WATCAL was developed around the modeling and estimation strategy discussed in the previous sections and has been designed for implementation on an IBM PC-compatible microcomputer. WATCAL is designed to be totally compatible with WATFORE; the final output of WATCAL is a system file containing the estimated values of the model parameters and other configuration parameters which is used by WATFORE during execution of a forecast. WATCAL is composed of six separate modules written in the BASIC and FORTRAN languages (see Figure 4.1):

(1) Control Module - this BASIC subprogram (WATCAL) handles communications between modules and, when the parameter estimates are acceptable to the user, writes them to the file SYSTEM.DAT, used by WATFORE.

(2) File Building Module - this BASIC subprogram (FILEBILD) allows the user to specify up to three years of sequential daily data contained in files of the WATFORE format and combine them into the estimation data set in file DAILY.DAT.

(3) Trend Estimation Module - this FORTRAN subprogram (REGRESS) estimates the parameters of the long-term trend equations using a form of the Marquardt algorithm. Monthly data is input; trend slope and intercept values in terms of daily water use are output.

(4) Fourier Series Estimation Module - this module is made up of two subprograms: the first (FOURIER), written in BASIC, calculates initial estimates of the Fourier series seasonal water use function using the discrete Fourier transform (DFT) (equations 4.2). The second subprogram (SEASON), written in FORTRAN, uses the results of the DFT as initial estimates of the parameters of a more complex potential water use function (equation 4.3) and iterates for the final estimates of Fourier series and rainfall function parameters using the Marquardt algorithm.

(5) Short-Memory Estimation Module - this FORTRAN subprogram (ESTIM), the largest and most computation-intensive module in WATCAL, estimates the short-memory parameters for temperature, day-of-the-week, and noise

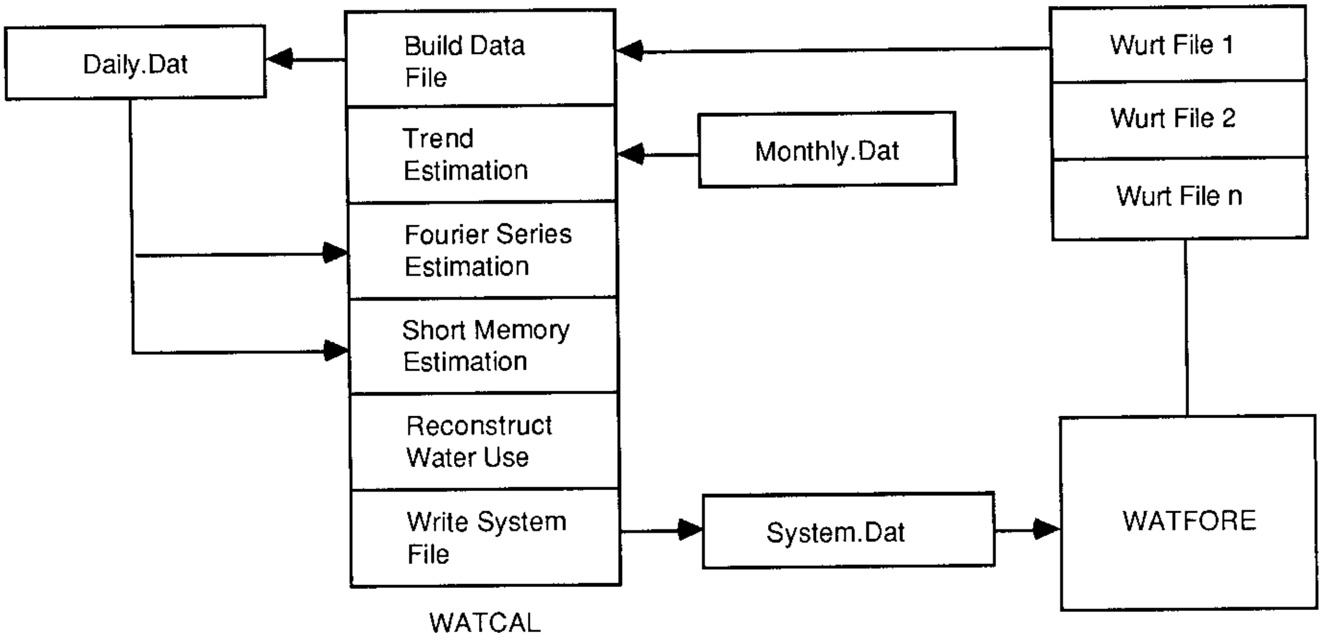
effects; the Marquardt algorithm is used.

(6) Graphics Module - this BASIC subprogram (RECON) may be called after any estimation step to graphically reconstruct that portion of the water use modeled so far. Twelve-month or two-month graphs of reconstructed and actual water use may be chosen.

After each estimation stage, the new estimates are written to a system file (CALIB.DAT) used by WATCAL, a second file (RECON.PRN) used by the graphics module, and to the computer screen. The previous or initial estimates are also shown on the screen for comparison. Final parameter estimates along with their standard errors and other diagnostics are also written to an estimation summary text file (OUTPUT.REG for long-term trend estimation and OUTPUT.EST for short-memory estimation). The overall program flow is depicted in Figure (4.1). For greater standardization and compatibility between programs, the user interface and option screens in WATCAL were designed so that their appearance and operation matches those of the WATFORE program.

Figure 4.1

WATCAL, Program Flow



5. APPLICATION TO CONSERVATION ANALYSIS

One particularly promising application of the WATFORE modeling and estimation strategy that emerged during the course of this research is the ability to quantitatively and graphically assess the effects of water conservation on daily water use. Shaw and Maidment (1986a) demonstrate that the effects of water use restrictions during conservation periods in Austin, Texas can be accounted for by adding dummy or "intervention" terms to the WATFORE model. The coefficients of the intervention terms are then estimated along with the short-memory parameters to give a numerical estimate of the average drop (or increase) in water use due to conservation. Shaw and Maidment (1986b) also apply this methodology to daily water use time series in Corpus Christi, Texas under severe water use restrictions during the summer of 1984 and introduce a method for reconstructing the water use series as if conservation had not occurred. This graphical reconstruction, when compared with a plot of actual water use during the same period, provides a visual indication of the impact of conservation programs.

An overview of the methodology for assessing the impact of conservation on daily water use and some results of the studies in Austin and Corpus Christi is presented in the following sections. Details of the background, theory, and specific conclusions and recommendations of studies in Austin and Corpus Christi, as well as an extensive literature review of conservation impact assessment techniques are given by Shaw (1986). Since these studies are straightforward applications of the WATFORE modeling and estimation strategy, the programs WATFORE and WATCAL could be used by municipalities, water-supply agencies, or consultants to perform similar conservation impact analyses for other cities.

5.1 Intervention Analysis

Box and Tiao (1975) suggest that a time series, y(t), may be modeled as:

$$y(t) = f(\kappa,\zeta,t) + N(t) \tag{5.1}$$

where,

$f(\kappa,\zeta,t)$ allows for deterministic effects of time, t, and effects of exogenous input variables, ζ, including interventions.

κ is a set of unknown parameters

$N(t)$ is stochastic background noise.

Hipel, et. al. (1975) formulate equation (5.1) for a series with a single intervention and no other exogenous inputs as:

$$y(t) = y^*(t) + N(t) \tag{5.2}$$

where, $$y^*(t) = \frac{\omega(B)}{\delta(B)} B^b I(t) \tag{5.3}$$

and,

$y^*(t)$ = the dynamic response of the process y(t) to an intervention "event"

$I(t)$ = a pulse function input representing the occurrence or ono-occurrence of the event:

$I(t) = 0$, when event is not occurring

$I(t) = 1$, when event is occurring

$\omega(B)$ = a linear filter applied to current and previous values of I

$\delta(B)$ = a linear filter applied to current and previous values of y^*

B = backshift operator such that $B(I(t)) = I(t-1)$

b = the delay in time for I to affect y^*

For a simple step response , without delay in response (i.e., b=0), equation (5.3) simplifies to:

$$y^*(t) = \omega_0 I(t) \tag{5.4}$$

In the context of an intervention which extends over several time intervals, the parameter ω_0 is interpreted as the average response over the entire event duration. Clearly, if the response y^* is to be interpretable, then the onset and duration of the event must be specified a priori. In order to account for interventions in the daily water use model, then, intervention response terms are added to the tranfer function noise model for short-memory water use (equation 3.7):

$$W_S(t) = \mu + \frac{\omega_0{}^T}{1-\phi_1{}^T B} T(t) + \sum_{i=1}^{v} y^*(t) + N(t) \tag{5.5}$$

where,

$y^*(t)$ = intervention response term of the form of equation (5.3)

v = number of interventions affecting the series

$$N(t) = \frac{1}{1-\phi_1-\phi_2 B^2-\phi_7 B^7} a(t) \text{ as in equation (2.2)}$$

5.2 Experiment Design

5.2.1 Conservation Restrictions. The cities of Austin and Corpus Christi, Texas were two of the largest cities in Texas to implement mandatory water use restrictions in response to the hot, dry summers of 1984 and 1985. Shaw (1986) gives a complete history of water conservation programs and ordinances in these two cities during the 1980's as well as physical descriptions of their water supply and distribution systems.

In Austin, during the summers of 1984 and 1985, three different stages of water use restrictions were implemented: (1) stage 1 restrictions called for voluntary compliance with stage 2 restrictions, (2) stage 2 restrictions limited lawn watering to a seventeen-hour period overnight and during the early morning on a designated watering day (once every five days according to the last digit of a property's street address); compliance with stage 2 restrictions was mandatory, (3) stage 3 restrictions (also mandatory) further limited lawn watering to a seven-hour period on the designated watering day. The periods of implementation for each stage of restrictions in Austin during 1984-85 are shown in table 5.1.

In addition to restrictions on watering hours, homes and

Table 5.1 - 1984-1985 Water Management History

Austin, Texas

EVENT	DATE
Begin Voluntary Conservation (stage 1)	May 10, 1984
Begin Mandatory Conservation (stage 2)	July 16, 1984
Return to Stage 1 Conditions	August 18, 1984
End Voluntary Conservation (stage 1)	September 30, 1984
Begin Voluntary Conservation (stage 1)	May 1, 1985
Begin Mandatory Conservation (stage 2)	July 31, 1985
Begin Mandatory Conservation (stage 3)	August 11, 1985
Return to Stage 2 Conditions	August 20, 1985
Return to Stage 3 Conditions	August 22, 1985
Return to Stage 1 Conditions	September 12, 1985
End Voluntary Conservation (stage 1)	September 30, 1985

businesses were allowed to water once every five days (within the hours allowed by the particular conservation stage) according to the last digit of the street address. During the summer of 1984 the five-day watering cycle allowed for properties with addresses ending in 0 or 1 to water the first day, 2 or 3 the second day, 4 or 5 the third, 6 or 7 the fourth, and 8 or 9 the fifth; the cycle would then begin again. On some lawn-watering days, water use was significantly higher than on others because large corner lots and businesses which have larger watering requirements, typically have lower address numbers; there are fewer properties, and correspondingly less water use, for the higher address numbers ending in 8 or 9. In 1985, the watering scheme was altered so that the five days in the cycle corresponded to properties with addresses ending in 1 or 2, 3 or 4, 5 or 6, 7 or 8, and 9 or 0.

In Corpus Christi, water use restrictions were first implemented during the summer of 1984 and remained in effect through the rest of 1984 and into 1985. During this time, three separate stages, or conditions, of water use restrictions were implemented: (1) condition 1 called for voluntary limitations on outdoor water use, (2) condition 2 restrictions put mandatory limits on allowable watering hours and limited watering to a designated day, once every ten days, as well, (3) condition 3 restrictons implemented water rationing on a monthly basis; also, during 1984, under condition 3 a total ban on outdoor water use was implemented. The periods of implementation for the various restrictions are given in Table (5.2).

5.2.2 Intervention Experiments. A number of intervention experiments were designed in order to analyze different aspects of the water conservation policies in Austin and Corpus Christi. These

TABLE 5.2 - 1984-1985 Water Conservation History

Corpus Christi, Texas

EVENT	DATE
Begin Voluntary Conservation (Condition 1)	May 17, 1984
Begin Mandatory Conservation (Condition 2)	July 1, 1984
Begin Mandatory Water Rationing (Condition 3)	August 25, 1984
Some Condition 3 Resrtictions LIfted	October 30, 1984
Mandatory Water Rationing Lifted	September 24, 1984
Return to Condition 2 Restrictions	January 22, 1985

experiments are summarized in Tables [5.3(a)] and [5.5(a)].

Interventions due to various periods of water use restrictions were modeled as zero-order intervention transfer functions as in equation (5.4):

$$y^*(t) = \omega_0 I(t) \tag{5.6}$$

where I(t) = 1 during restriction periods and zero elsewhere.

A more complicated intervention term was included for investigation of the effects of a five-day lawn watering cycle in Austin:

$$y^*(t) = (\omega_0 + \omega_1 B + \omega_2 B^2 + \omega_3 B^3 + \omega_4 B^4)\ I(t) \tag{5.7}$$

where I(t) = 1 on days when properties with addresses ending in 0 and 1 (1984) or 9 and 0 (1985) were allowed to water. Elsewhere, I(t) = 0. This intervention function is of the same form as the function which accounts for weekly cycles disscussed in Section 3.1.2 (equation 3.6). However, the period of the watering cycle in Austin is only five days, rather than seven days for the weekly cycle, so only five days of lag terms are included in the function above. Rainfall and temperature data were taken from National Weather Service records for each city; input from a single rain gage within a city is used in each case. Parameters were estimated using the procedures discussed in the previous chapters of this report.

5.3 Results

5.3.1 Austin. Results of parameter estimation for intervention

TABLE 5.3 - Intervention Experiments

Austin, Texas

(a)

Experiment	Comments	I_1	I_2	I_3
A1 (1984)	voluntary vs. mandatory	stage 1 (5/10-7/15)	stage 2 (7/16-8/17)	stage 1 (8/18-9/30)
A2 (1985)	overall effectiveness	entire mandatory (7/31-9/12)	-	-
A3 (1985)	stage 3 vs. stage 2	all stage 2 (7/31-8/10) (8/20-8/21)	all stage 3 (8/11-8/19) (8/22-9/12)	-
A4 (1985)	independent assessment of each stage 2	stage 2 (7/31-8/10)	all stage 3 (8/11-8/19) (8/22-9/12)	stage 2 (8/20-8/21)
A5 (1985)	treats latter stage 2 as a stage 3	stage 2 (7/31-8/10)	all other (8/11-9/12)	-

(b)

Experiment	ω_{01} (MGD)	ω_{02} (MGD)	ω_{03} (MGD)
A1	-2.77 [4.14]	-13.45 [6.8]	-1.27 [1.9]
A2	-5.5 [7.75]	-	-
A3	-6.7 [6.99]	-4.4 [6.23]	-
A4	-9.6 [7.87]	-3.0 [6.43]	+0.4 [11.3]
A5	-9.6 [7.77]	-2.8 [6.28]	-

values in brackets are the standard errors of the estimates

TABLE 5.4 - Parameter Estimation, Five-day Watering Cycle

Austin, Texas

(a) 1984

Address Ends In	Coefficient	Estimate (MGD)	Std Error (MGD)
0-1	ω_{03}	2.35	4.80
2-3	ω_{13}	0.88	4.89
4-5	ω_{23}	-1.35	4.97
6-7	ω_{33}	-3.22	4.90
8-9	ω_{43}	-4.42	4.80

(b) 1985

Address Ends In	Coefficient	Estimate (MGD)	Std Error (MGD)
9-0	ω_{03}	-6.1	7.71
1-2	ω_{13}	-11.0	8.29
3-4	ω_{23}	-8.6	8.43
5-6	ω_{33}	-6.8	8.39
7-8	ω_{43}	-0.5	7.75

experiments on summer 1984 and summer 1985 data are shown in Tables (5.3) and (5.4). Standard errors of the estimates are also reported. Other transfer function parameter values for equation (5.5) not shown in the tables were comparable to those estimated by Maidment, et. al., (1985b).

Thus, for 1984 (experiment A1), it is estimated that conservation reduced water use by 2.77 MGD during the first stage 1 voluntary conservation period, by 1.27 MGD during the second stage 1 voluntary conservation period, and by 13.45 MGD during the stage 2 mandatory conservation period after departures from normal weather conditions have been accounted for in these periods. These results are consistent with the results of the regression analysis reported by Nvule and Maidment (1985).

For 1985, in experiment A2, it is estimated that the entire mandatory restriction program (stage 2 and stage 3 combined) reduced water use by an average of 5.5 MGD. When the results of experiments A1 and A2 are compared, it appears that mandatory water use restrictions were less effective during the summer of 1985 than in the summer of 1984. A possible explanation for this behavior offered by Austin water officials is that the amount of water conserved is less when water use and air temperature prior to conservation are at high levels, than when water use and air temperature prior to conservation are lower. Indeed, the average daily maximum temperature during mandatory restrictions in 1984 was 96.1° F. while during the 1985 mandatory restrictions, the average temperature was 98.2° F. Thus, the 1985 conservation program was required to hold down a much stronger demand for water than was the case in 1984. However, such a year-to-year comparison must be interpreted with a degree of caution, as will be discussed later.

For 1985, the results of experiment A3, comparing the effects of stage 2 and stage 3 restrictions, show an average decrease of 6.7 MGD and 4.4 MGD, respectively, over the periods each of these restrictions was in effect. Thus, the stage 3 policy may be less effective than the less restrictive stage 2 policy for 1985. While average daily maximum temperatures during stage 2 tended to be higher than those during stage 3 (99.3° F. versus 97.8° F.), much of the conservation during stage 2 occurred during the early part of that period when temperatures were lower. Again, it is possible that conservation effects were greater when water use is lower prior to implementing restrictions. Also, city officials observed that the tighter stage 3 restrictions may have pushed water users "too far", so that actual compliance with these restrictions was less than for stage 2 restrictions.

Independent estimation of the impact of the brief stage 2 period of August 20-21 (experiment A4) was inconclusive due to the short length (2 days) of this restriction period. A mean increase of 0.4 MGD was estimated for the two-day period, while the standard error of the estimate was 11.3 MGD; thus the estimate is insignificant.

In experiment A5, it was assumed that this second brief stage 2 period was part of a stage 3 period lasting from August 11 to September 12. Results of this experiment show an estimated average decrease of 2.8 MGD during the stage 3 period and a decrease of 9.6 MGD during the stage 2 period from July 31 to August 10.

Results of parameter estimation for equation (5.7) (the five-day watering scheme) must be interpreted independent of other conservation effects. Thus, the parameter values must be compared to the average water use over the five-day cycle. Figures (5.1) and (5.2) show the five-day watering cycles from 1984 and 1985 data. Each ordinate in the graph is computed by subtracting the response calculated for a given watering day from the average response during the entire mandatory restriction program for that year (i.e. 13.45 MGD in 1984, 5.5 MGD in 1985). The behavior illustrated in Figures (5.1) and (5.2) shows a large imposed five day water use cycle of more than 10 MGD in 1985. This imposed cycle was detrimental to the program objective of reducing peak usage and suggests a strategy for smoothing the five-day cycle. If each of the two address numbers for a given watering day is assumed to contribute equally to that day's departure from the average (e.g., addresses ending in 1 contribute 2.2 MGD and addresses ending in 2 contribute 2.2 MGD to the total 4.4 MGD departure on the 1-2 watering day for 1985), then the ordinates of Figures (5.1) and (5.2) may be separated and recombined in order to minimize the amplitude of the five-day cycle. A recommended watering scheme based on this type of recombination is presented in Figure (5.3). In effect, the recommended scheme combines addreses whose last digits sum to 9, i.e., 9-0, 1-8, 2-7, 3-6, and 4-5. It can be seen in Figure (5.2) that one address pair (9-0) which actually followed this scheme in 1985 had a very small departure from the average water use pattern.

This altered watering scheme arising from this research project was implemented during the 1986 water conservation program and proved effective in smoothing out the five day cycle in water use. During mandatory conservation in summer 1986, the average amplitude of the five-day watering cycle (i.e., the difference in water use between the

Figure 5.1 - Five-Day Watering Cycle, Austin, Texas, Summer 1984

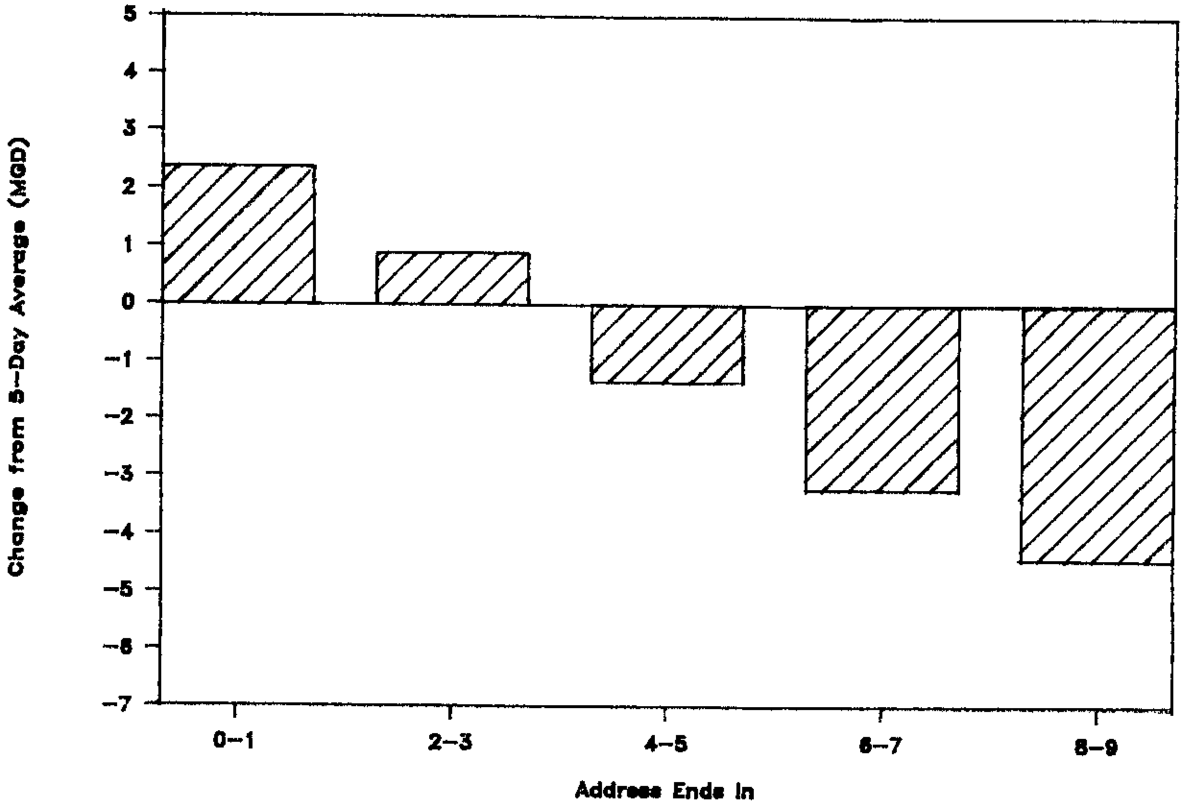


Figure 5.2 - Five-Day Watering Cycle, Austin, Texas, Summer, 1985

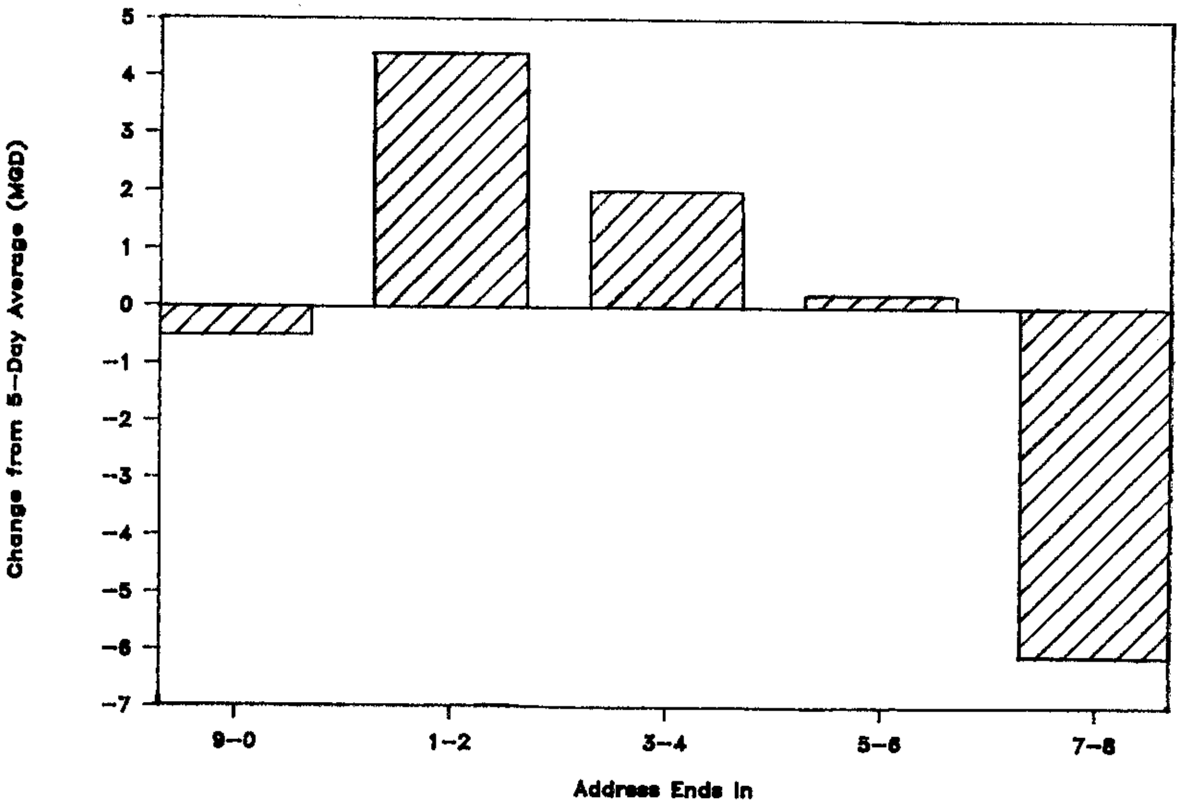


Figure 5.3 - Recommended Watering Scheme, Austin, Texas

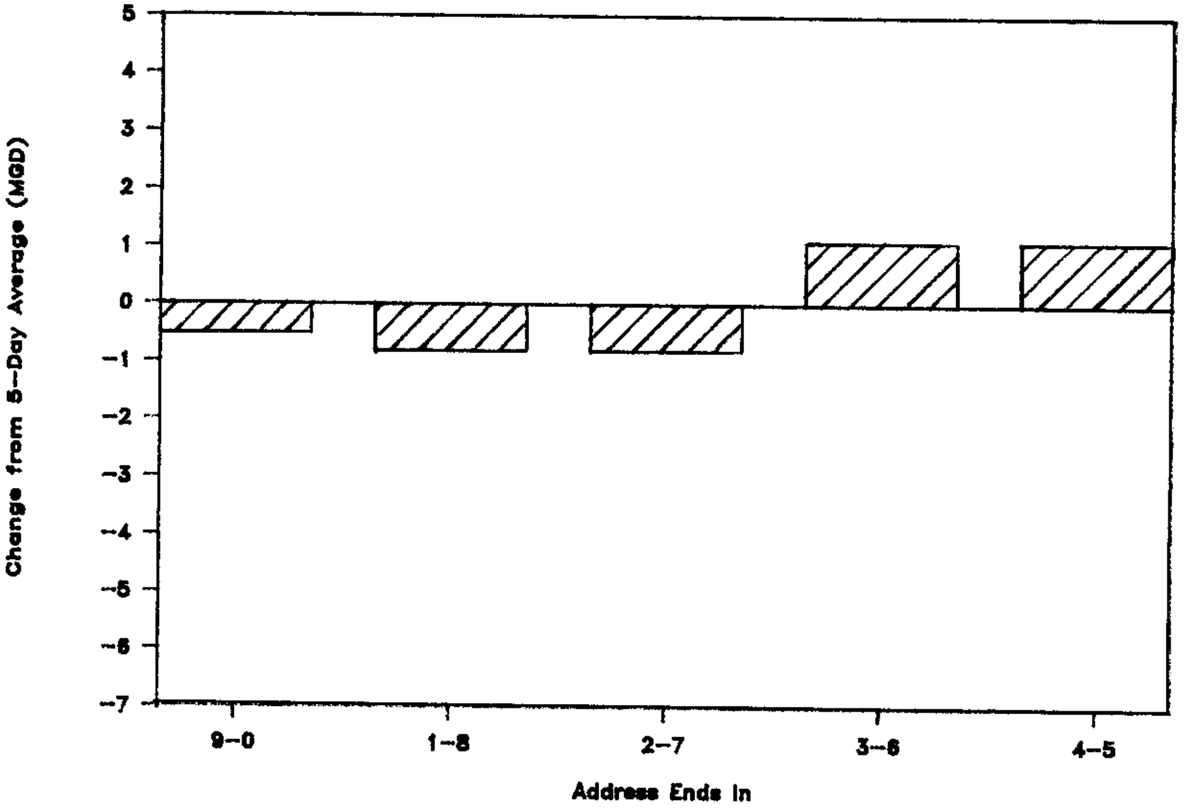
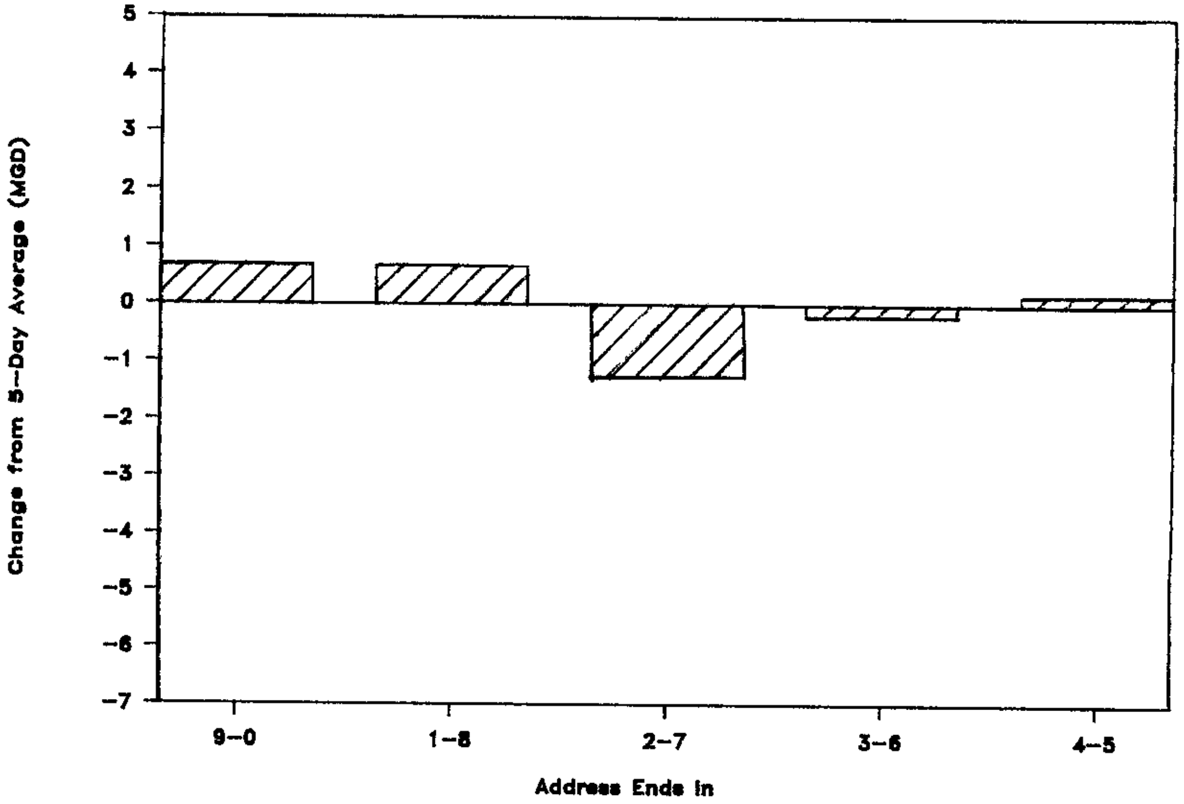


Figure 5.4 - Five-Day Watering Cycle, Austin, Texas, Summer 1986



maximum and minimum days in the cycle) was only 1.91 MGD, compared to 6.77 and 9.5 MGD for 1984 and 1985, respectively (Nvule and Maidment, 1987). Figure (5.4) shows the observed watering cycle for 1986. City officials also had feared that the pairing of separated address numbers (e.g., 1-8 instead of 1-2) would confuse citizens but these fears proved groundless.

5.3.2 Corpus Christi. Parameter estimates for three periods of water use restrictions in Corpus Christi during 1984 are shown in Table [5.5(b)]. Voluntary conservation (Condition 1, experiment CC1, ω_{01}) appears to have had little or no effect on daily water use, the estimated impact during this period (+0.01 MGD) being near zero; this agrees with the results for Austin reported above, where voluntary conservation during 1984 was shown to have insignificant impact on daily water use. The impact of mandatory restrictions beginning July 1, however, was quite significant. Condition 2 restrictions from July 1 - August 24, 1984 were estimated to have caused an average decrease of 28.6 MGD in daily water use; the various forms of Condition 3 restrictions in place from August 25 through November 20 caused water use to be decreased 25.4 MGD on average. Experiment CC2 was designed to assess the overall effectiveness of mandatory programs during 1984, treating the period July 1 - November 20 as a single intervention: the average impact during this period was a decrease of 27.2 MGD.

5.3.3 Reconstruction of Water Use Series. Using equations (3.5) and (3.7), a water use series for a year when conservation programs were in effect can be reconstructed, as if no conservation had

TABLE 5.5 - Intervention Experiments

Corpus Christi, Texas

(a)

Experiment	Comments	I_1	I_2	I_3
CC1	effectiveness of each restriction period	5/1-6/30 1984	7/1-8/24 1984	8/25-11/20 1984
CC2	overall effectiveness of mandatory restrictions	7/1 - 11/20 1984	-	-

(b)

Experiment	ω_{01} (MGD)	ω_{02} (MGD)	ω_{03} (MGD)
CC1	+0.01 [2.84]	-28.58 [3.89]	-25.44 [3.40]
CC2	-27.24 [2.73]	-	-

values in brackets are the standard errors of the estimates occurred, using model parameters estimated from data prior to that year. Such a reconstruction is, in essence, a forecast of the 365-day pattern of daily water use and can be compared with observed water use during the year in order to visualize the effects of conservation on a daily basis. The impact of conservation could be determined as the difference between forecasted (assuming no conservation) and observed water use. On a day-by-day basis, then, the impact of conservation is simply the difference between the ordinates of the two plotted curves in each of Figures (5.5) through (5.10).

For the reconstructions, parameters were estimated using data from 1980-1982 (1980 and 1982 were hot, dry years similar to 1984 and 1985; 1981 rainfall and temperatures were about normal). Actual temperature and rainfall data from 1984-1985 were used in the reconstruction. Values of the model parameters are given in Table (5.6). Enlarged views of the summer period in Austin (May 1 - October 1) are shown for each year (Figures 5.6 and 5.8). In 1984 (Figure 5.5) the only period in which the observed water use in Austin goes significantly below the modeled conditions is during mandatory (stage 2) conservation. The decrease during this period agrees, approximately, with the intervention estimate of about 13 MGD. Again, in 1985 (Figure 5.8), Austin water use dips slightly below the modeled water use during the periods of stage 2 and stage 3 mandatory restrictions. The average decrease during the stage 2 period appears to be greater than during the stage 3 period; this result agrees with the intervention estimates of stage 2 versus stage 3 in 1985. The fact that many of the intervention estimates were not statistically significant for 1985 is supported by the almost insignificant impacts of conservation shown in

Figure 5.5 - Observed and Reconstructed Daily Water Use

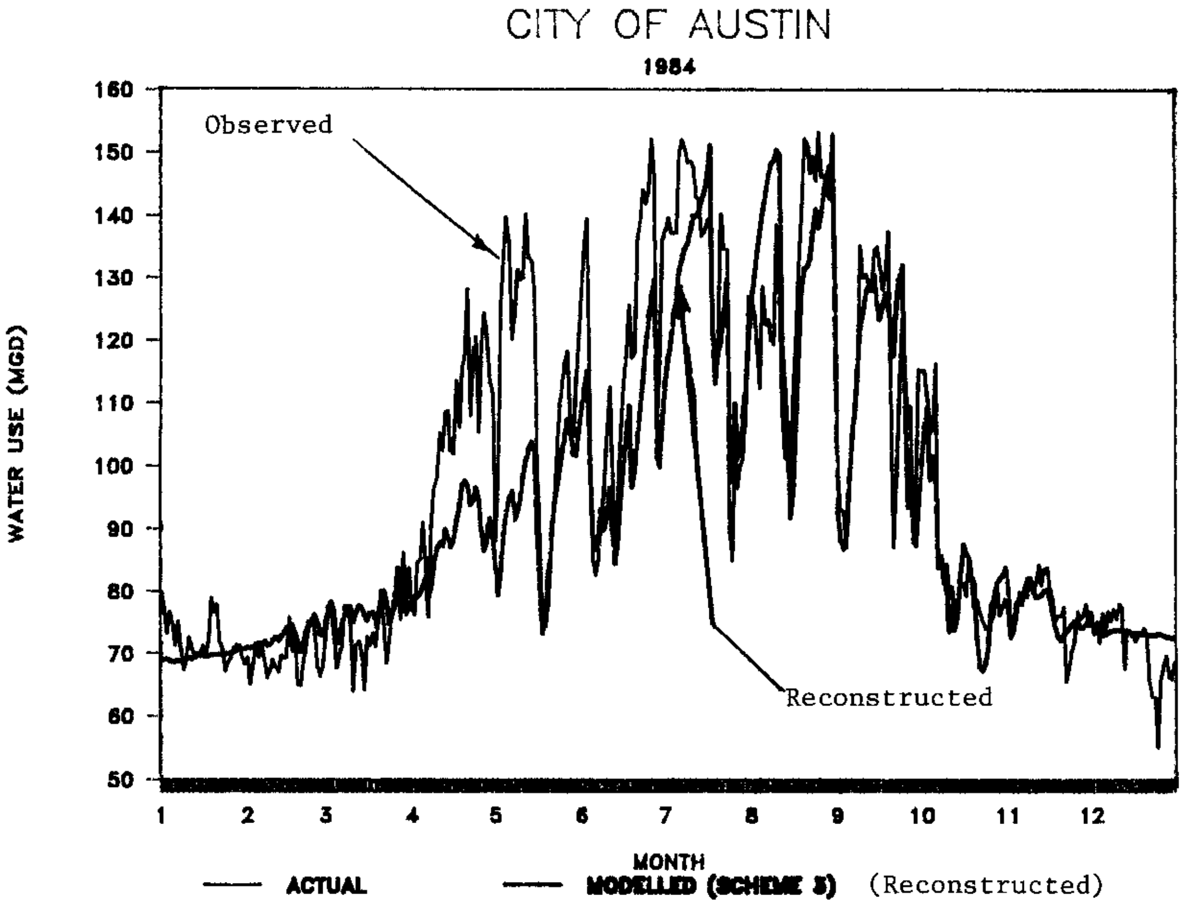


Figure 5.6 - Observed and Reconstructed Daily Water Use

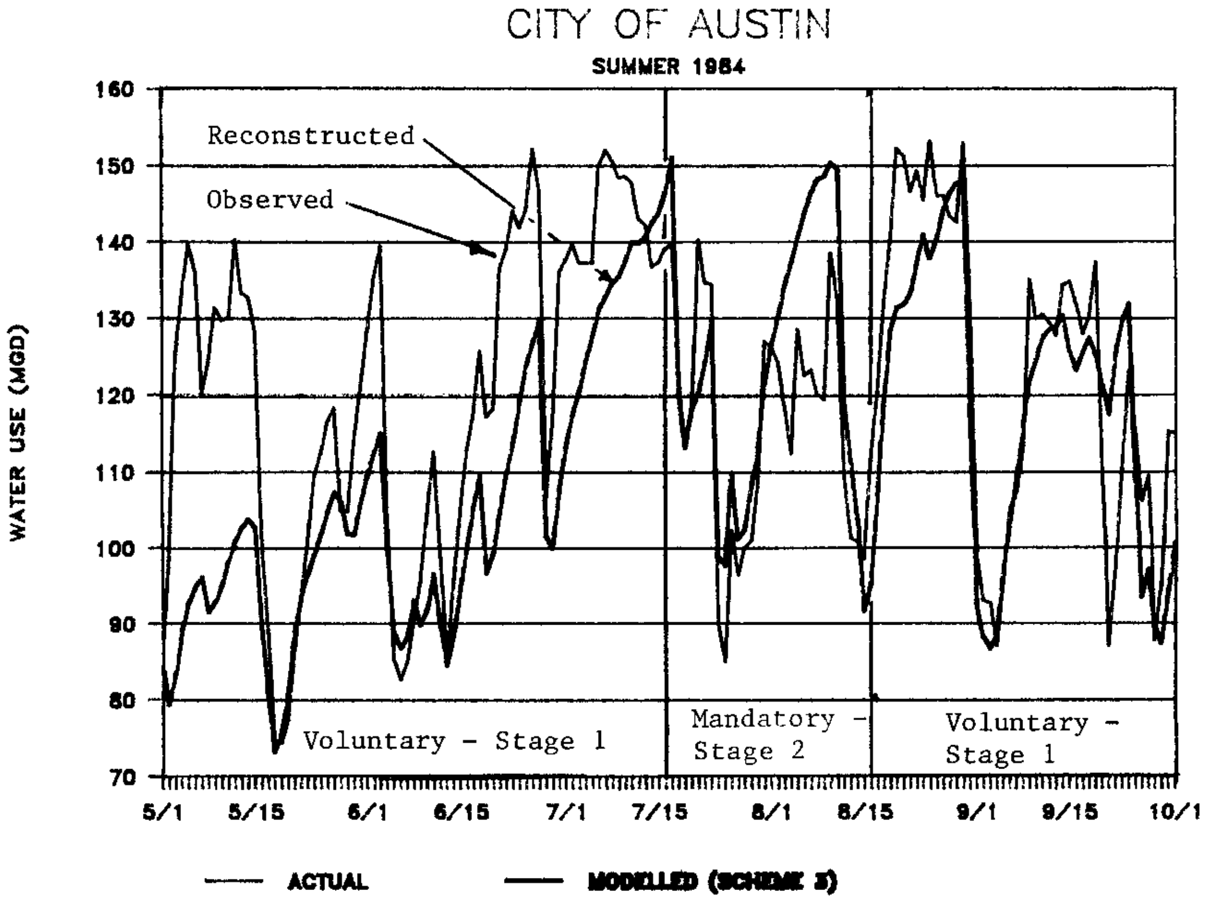


Figure 5.7 - Observed and Reconstructed Daily Water Use

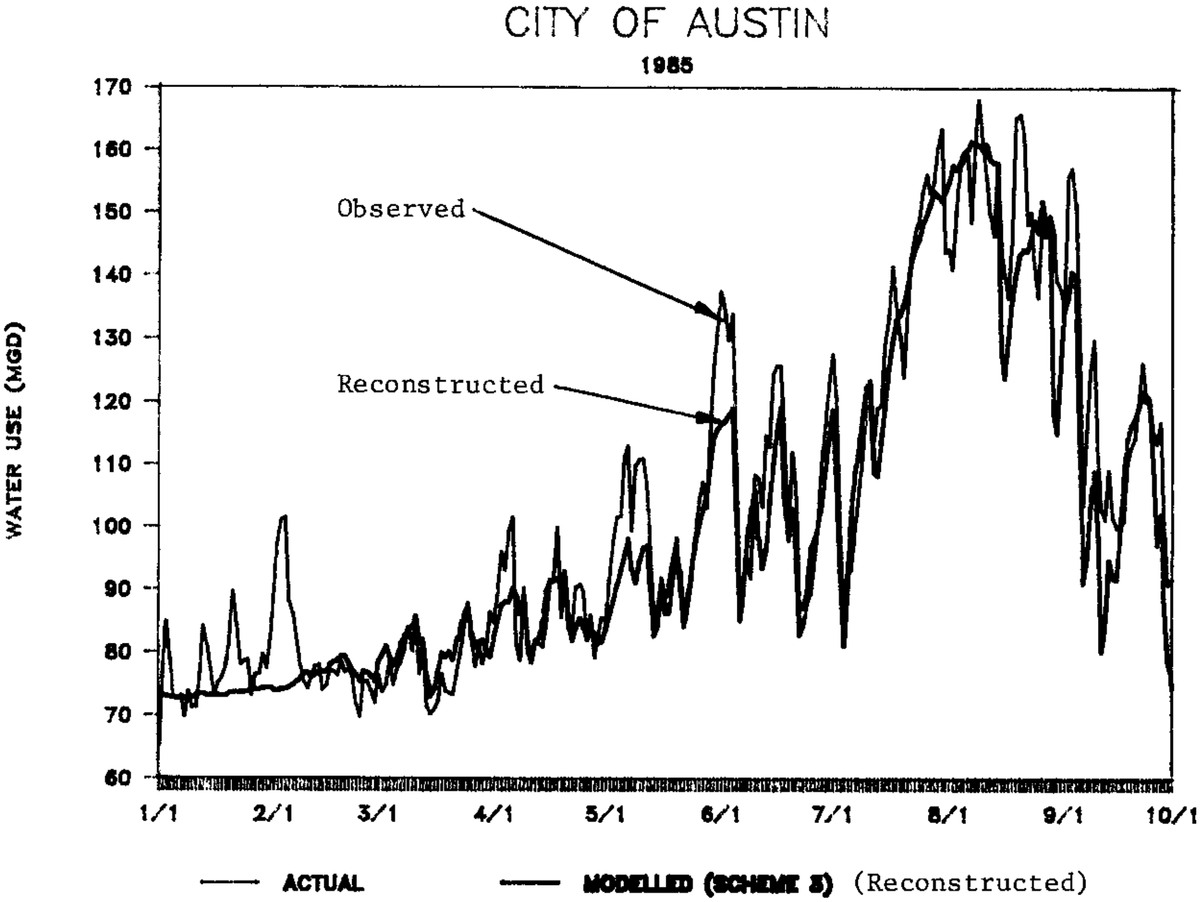


Figure 5.8 - Observed and Reconstructed Daily Water Use

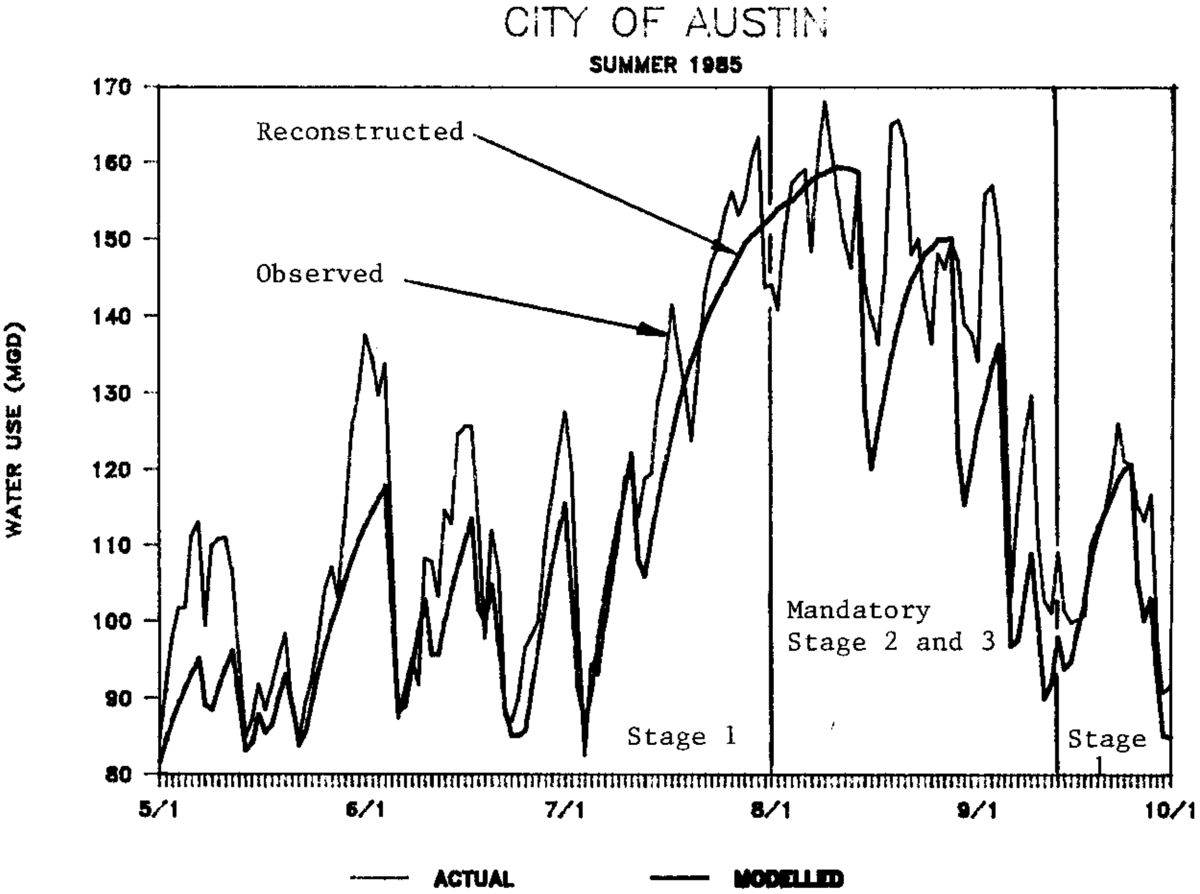


Figure 5.9 - Observed and Reconstructed Daily Water Use

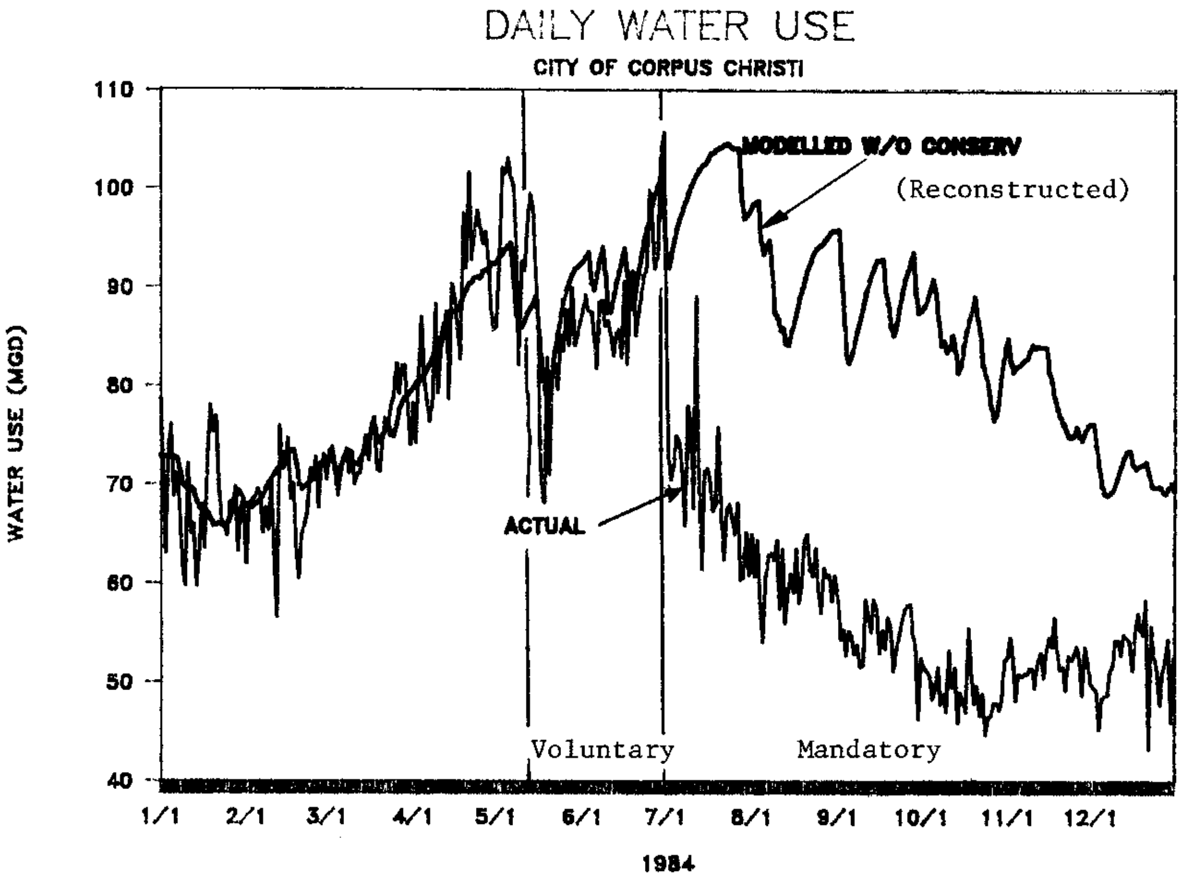


Figure 5.10 - Observed and Reconstructed Daily Water Use

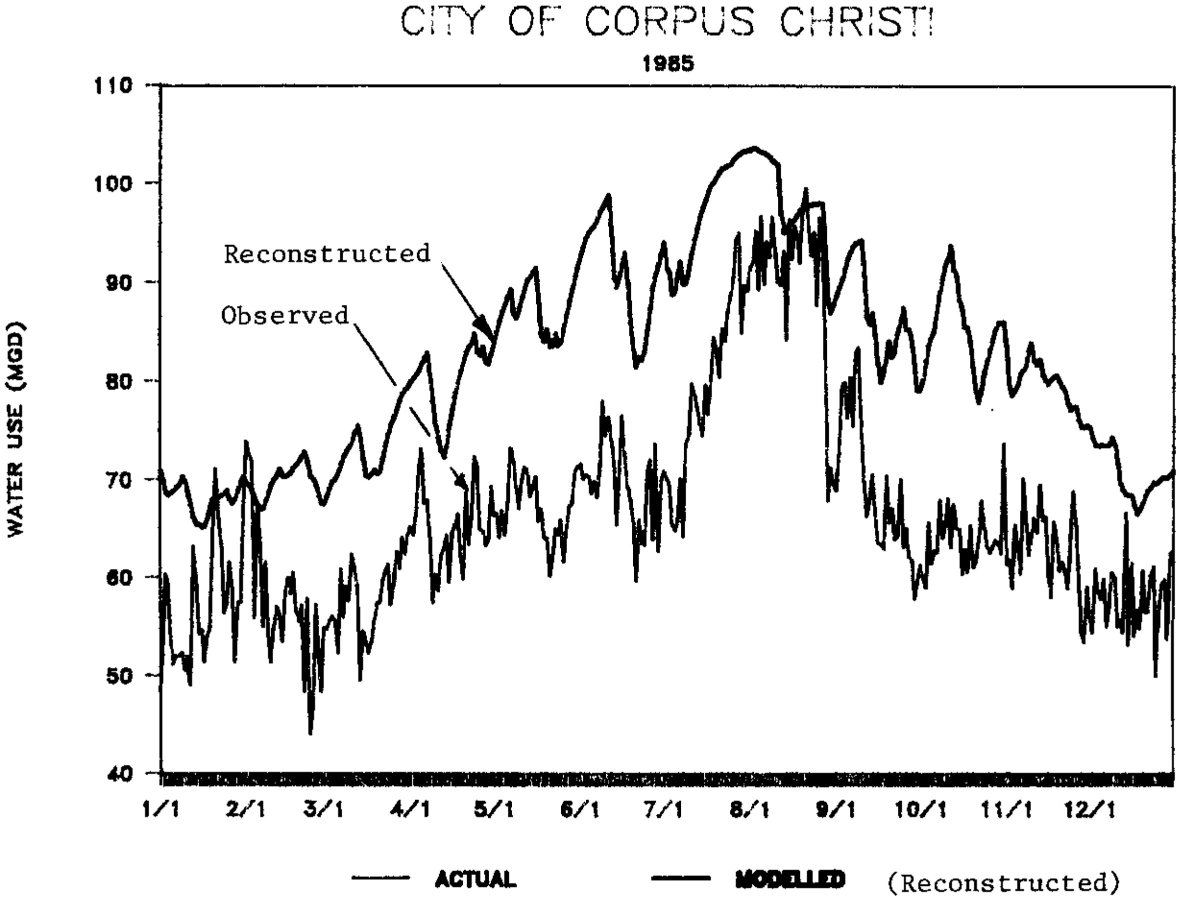


TABLE 5.6 - Heat Function Parameters

PARAMETER	AUSTIN	CORPUS CHRISTI
a_0	.362	.320
a_1	-.373	-.136
b_1	-.173	-.079
a_2	-.030	-.012
b_2	.102	-.036
a_3	.021	-.025
b_3	-.003	.008
a_4	.005	.002
b_4	-.013	.021
ω_0^R	-.362	-.112
ω_1^R	.144	.054
δ_1^R	.866	.906
ϕ_1	.817	.786

Figure (5.8). It is interesting to note that the five-day watering cycle in Austin can be clearly seen (especially in 1985) in the plots of actual water use. The cycle appears as a regular variation of amplitude 5-10 MGD about the potential use curve during conservation.

The effects of conservation in Corpus Christi are clearly visible in the reconstructions. The impacts of the three conservation periods shown in Figure (5.9) agree with the results of intervention analysis reported in Section 5.3.2: after July 1, the observed water use began to fall away, by early autumn of 1984 stabilizing at levels lower than those of the previous winter. The difference between reconstructed and actual water use during condition 2 and 3 restrictions was around 30 MGD; this agrees with an intervention estimate of 27.2 MGD during these periods (experiment CC2). In the figures, the difference between the areas under the reconstructed and the observed water use curves represents the estimated volume of water conserved. By this method, the volume of water conserved during Condition 2 restrictions is calculated to be approximately 31% of the total reconstructed water use during this period (i.e., Condition 2 restrictions resulted in a savings of 31% of what the water use would have been without conservation). Similarly, the volume of water saved during Condition 3 restrictions was approximately 39% of the total estimated water use without restrictions. Conservation during the voluntary Condition 1 period appeared to be negligible.

In Figure (5.10), the modeled and observed water use series are extended through 1985 in order to find out if conservation effects would taper off after some period of time (i.e., the modeled and observed curves would converge). However, as can be seen in the figure, the actual water use remained lower than the predicted levels during the entire year, suggesting that the model parameters may have changed permanently (most likely as a result of a decrease in the base water use levels). If attributable entirely to the conservation program of the previous year, the change in model parameters indicates that the public had, by 1985, altered their normal water using behavior towards conservation. Similar effects were noticed in several California communities following the severe drought of 1976-77 in that state (East Bay Municipal Utility District, 1985). In the East Bay Municipal Utility District (California), mandatory water conservation measures were implemented in 1977 during the height of the drought, causing a large decrease in total annual water use from the previous year. Although water use restrictions were lifted in late 1977, water use levels by the end of 1984 had not yet returned to pre-drought levels, this despite a steadily growing population.

5.4 Interpretation of Results

Intervention analysis and reconstruction using the WATFORE daily water use model are useful tools for quantifying the overall effectiveness of water conservation policies. However, results should be interpreted with a measure of caution. Intervention parameter values provide an estimate of the average aggregate change in daily water use during a restriction period. As such, this type of analysis gives little information on hourly peaks, daily peaks, or other factors which may be critical to the water management program. As an average effect, the intervention parameter also fails to reveal any change in the real impacts over time. For instance, actual conservation may vary according to the length of time that restrictions have been in effect, as water users acclimate themselves to the new conditions.

A possible explanation for the difference between the estimated impacts of Austin's mandatory restrictions in 1985 versus 1984 is that water users were by 1985 becoming comfortable with the regulations (that is, the "shock effect" of the first implementation of mandatory restrictions in 1984 had worn off by the summer of 1985). Also, conservation amounts may change day-to-day following public announcements by water officials during the course of a given conservation program (Nvule and Maidment, 1985). Additionally, some water utility officials have felt that conservation effects may vary with water use level prior to implementation of conservation (more conservation when use is high and less when use is low).

Special care must be taken when comparing the results of intervention analysis of one year to those of another. It is tempting to make a direct comparison between, for example, the impacts of Austin's mandatory restrictions in 1985 versus 1984. Such a comparison is quite reasonable if the transfer function and noise model parameters do not vary from year to year. However, experience in modeling water use series has shown that in some cases the parameters do tend to vary slowly with time (Miaou, 1986a). It should be recognized that the impact of an intervention is defined, in terms of equation (5.5), as the magnitude of the departure from "normal" conditions. Normal conditions in this context refer to water use during the period when restrictions were not in effect. Thus, in a case where it is suspected that model parameters are time-varying, a direct year-to-year comparison of impacts may lead to erroneous interpretations since different sets of "normal" conditions are actually being used in each year.

The parameter estimates for conservation program impacts reported in this study, while internally consistent, are in many cases not statistically significant when compared to their standard errors (this is especially true when estimating short interventions such as I_3 in experiment A4). These points illuminate the need for further research into quantitative methods for assessing the impact of conservation restrictions on daily water use. Development is needed of more rigorous statistical methods for determining overall effectiveness of conservation programs and a means of accounting for possible time-varying behavior of the intervention parameters. This chapter deals exclusively with off-line, ex-post facto analyses; i.e., all of the data must be available and conservation ended before an impact assessment is made. It would be desirable from a utility management standpoint to be able to assess the impact of conservation as it occurs (on-line) so that necessary adjustments to the system or the conservation program itself can be made. Miaou (1986a) has suggested a state-space formulation of the intervention model of equation 5.5 in which the intervention parameters are estimated on-line by an adaptive Kalman filter scheme. Such a formulation allows the intervention response to be either deterministic, following a pre-set form as in traditional intervention analysis, or stochastic, following a random walk process. Presently, further research is needed on the estimation capabilities of this model under different types of intervention conditions.

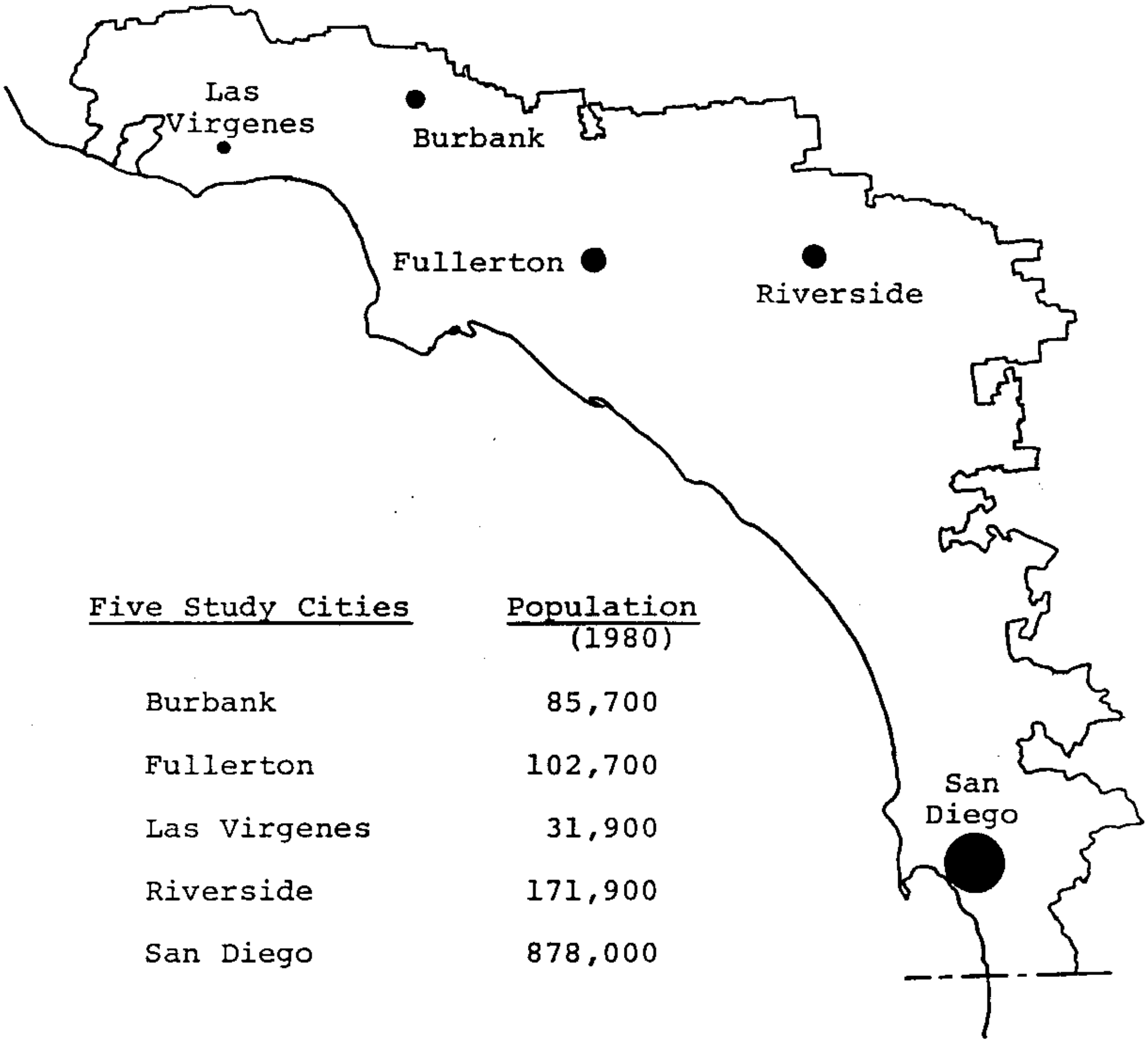
6. REGIONALIZATION OF THE WATFORE MODEL

6.1 Introduction

The Metropolitan Water District of Southern California is a regional water supply agency which takes water from northern California and the Colorado River via long distance water transfers and distributes it throughout the urbanized area of Southern California. The service area stretches from north of metropolitan Los Angeles through Orange County to San Diego and inland to Riverside County. Metropolitan supplies approximately half the total water demand of the region's 13 million inhabitants, the remainder being supplied from local surface and groundwater sources operated by individual cities and water districts. Through 27 member agencies, Metropolitan provides a supplemental supply to approximately 135 cities and water districts. This is possibly the largest regional water supply system involving long distance water transfers in the world.

To carry out a study of possible regional consistency of water use patterns, five cities were selected: Burbank, Fullerton, Las Virgenes, Riverside and San Diego, located as shown in Figure 6.1. The populations of these cities range from 31,900 at Las Virgenes to 878,000 at San Diego (these figures are averages for the period 1976-1985). The locations include both the coast (San Diego) and inland (Riverside) and locations in metropolitan Los Angeles and Orange County (Burbank and Fullerton). For each city, monthly water use records were obtained from July 1985 to June 1986 and accompanying records of monthly rainfall and monthly average maximum air temperature were

Figure 6.1 Location map for cities in the Metropolitan Water District of Southern California.



The Metropolitan Water District of Southern California

Five Study Cities	Population (1980)
Burbank	85,700
Fullerton	102,700
Las Virgenes	31,900
Riverside	171,900
San Diego	878,000

obtained from the National Weather Service. Likewise, daily records of each of these variables were obtained from 1980 to 1985 for each variable. The water use data employed are for end-use demand in the city; they do not include separate demand for agriculture. In the case of San Diego, for example, it is the water use of the City of San Diego (Metropolitan supply plus local supply) which is studied, rather than the usage pattern of the San Diego County Water Authority which includes a considerable agricultural component. Concurrent time series data for Metropolitan monthly water deliveries from 1975 to 1986 were obtained and also daily deliveries for 1985.

6.2 Monthly Time Patterns

The time pattern of monthly usage in the five cities, measured in acre-feet/month, is shown in Figure (6.2) for the calendar years 1976 to 1985. This period was chosen since it covered ten complete calendar years without missing data in any of the cities. It is evident from the figure that the demand follows a characteristic pattern, low in the winter and high in the summer with evidence of an upward trend in demand at all locations, especially in San Diego. A close similarity in shape of the demand pattern in any given year can also be seen in this figure, a similarity which is exploited more fully later. The data for Las Virgenes prior to 1980 can be seen to vary erratically unlike the more smooth variation observed at Las Virgenes after 1980. As it is considered that the pre-1980 data at Las Virgenes are not reliable, they are omitted in the subsequent graphs. The effects on the demand pattern of the 1976-77 drought can be seen as a higher base load over the winter of 1976-77 followed by lower than normal load

Figure 6.2 Monthly water use in the five cities.
1-Las Virgenes 2-Burbank 3-Fullerton 4-Riverside 5-San Diego

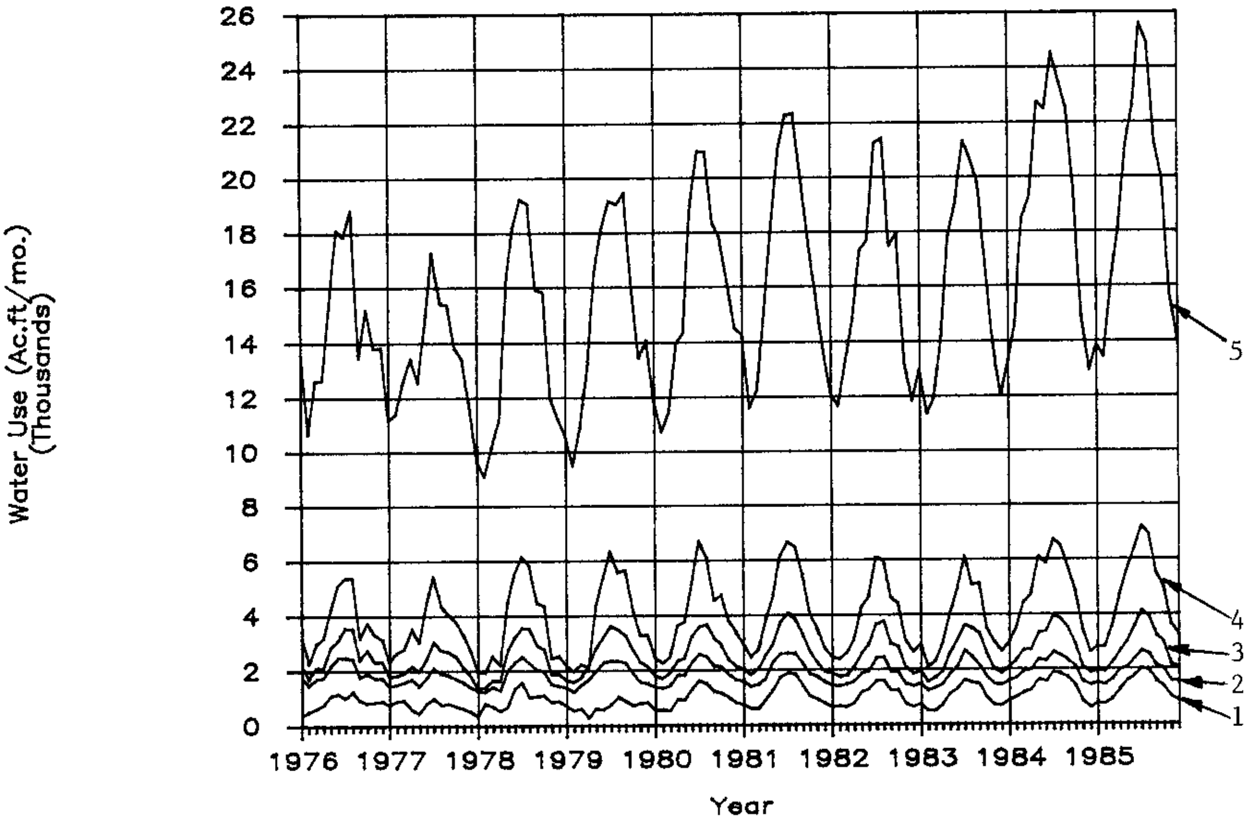
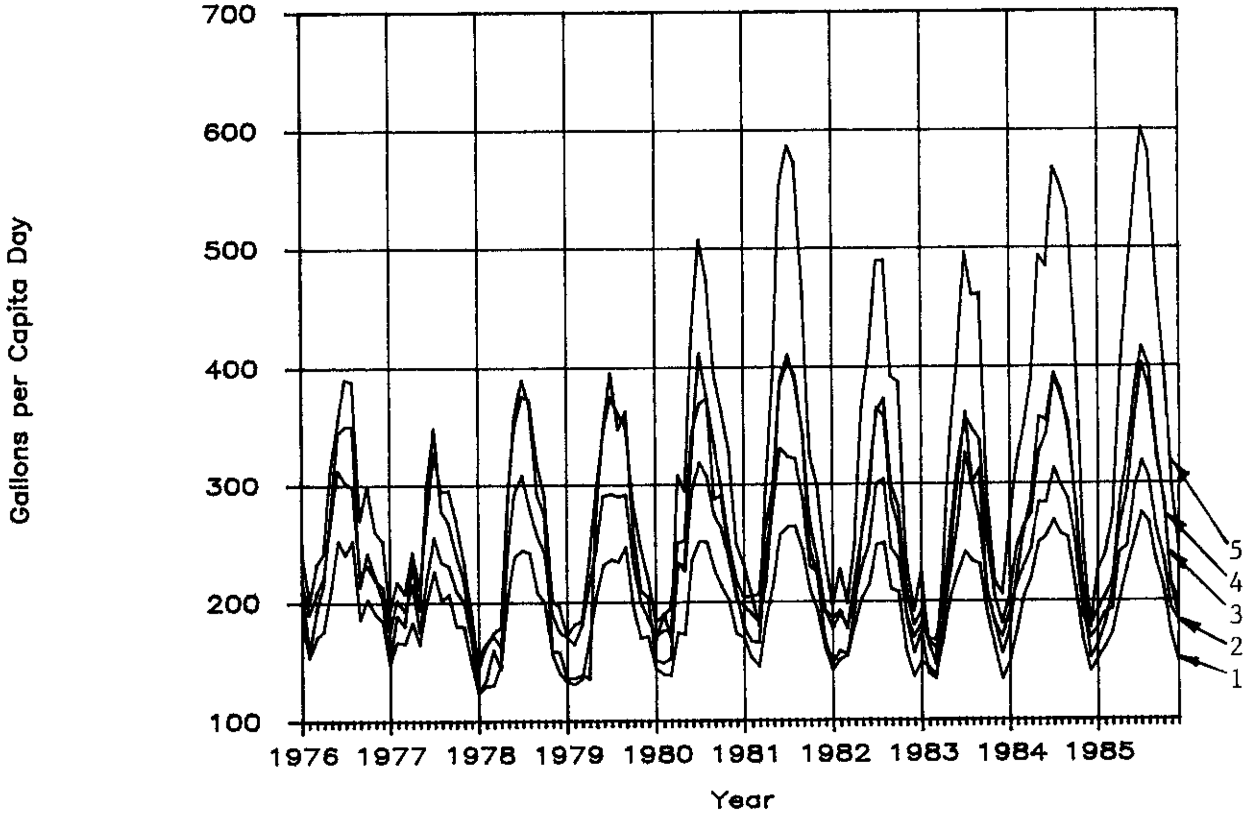


Figure 6.3 Per capita monthly water use in the five cities.
1-San Diego 2-Burbank 3-Riverside 4-Fullerton 5-Las Virgenes



during the following summer, perhaps as the result of conservation measures.

One way of bringing the data onto a common base is to convert them into per capita usage figures, in gallons per capita day. A smooth line was fitted to the census population data at each location, and the resulting monthly population estimates were divided into the monthly water use data to produce monthly time series of water use in gallons per capita day, as shown in Figure (6.3). In these plots, it can be seen that on a per capita basis the base use (represented by the minimum monthly use) is fairly consistent among the five cities while the seasonal use varies much more, being lowest in San Diego and highest in Las Virgenes; Fullerton and Riverside show very similar per capita usage characteristics while the pattern for Burbank lies between these two and that of San Diego. It is thought that the large seasonal variation in usage at Las Virgenes is the result of a considerable number of large landscaped lots that have automatic sprinkler systems.

Miaou (1987) fitted time trend lines to these per capita usage graphs. He fitted a base use line to the three minimum months (January, February and March), subtracted the base line from the total usage to leave the seasonal usage component, then fitted a maximum seasonal usage line to the three maximum summer months (June, July, August). In both cases the lines were fitted by linear regression against time and the effects of variations of temperature and rainfall from their normal values were corrected. The data for 1976-77 were omitted from the data set used for fitting the lines because of the effects of a severe drought occurring at that time, then the lines were extrapolated over that period as an estimate of what the base and maximum seasonal usage would have been in the absence of the drought.

6.3 Dimensionless Water Use

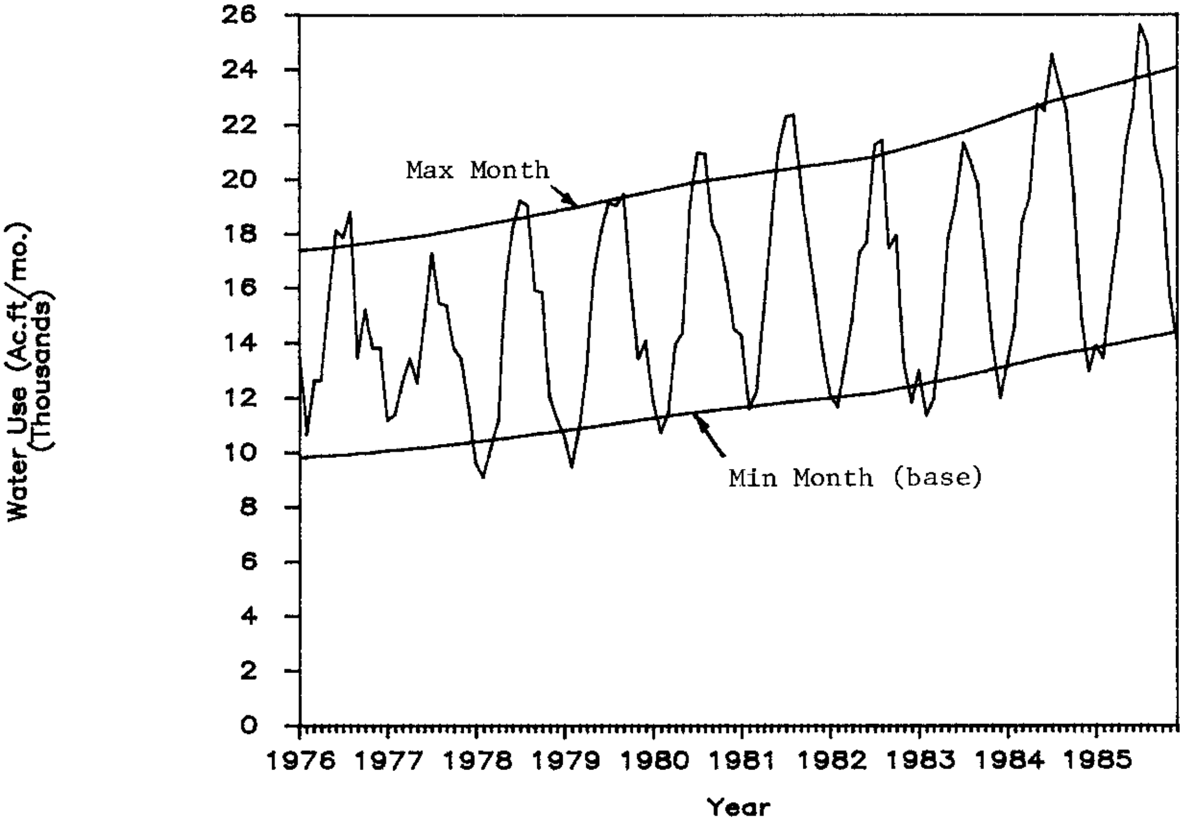
The fitted base and maximum seasonal trend lines of per capita usage can be converted into trend lines in water use (acre-ft/mo.) by multiplying by population, as shown in Figure 6.4(a) for San Diego. These trend lines estimate what the base use and maximum seasonal usage would have been if weather had been normal throughout the period. A dimensionless water use data series can be constructed by subtracting the base use from the observed usage and dividing the result by the maximum seasonal usage which is the difference between the two trend lines in Fig. 6.4 (a). This rescaling of the water use data series can be written as:

$$\text{Dimensionless water use} = \frac{\text{Observed Usage} - \text{Minimum month}}{\text{Maximum Month} - \text{Minimum Month}}$$

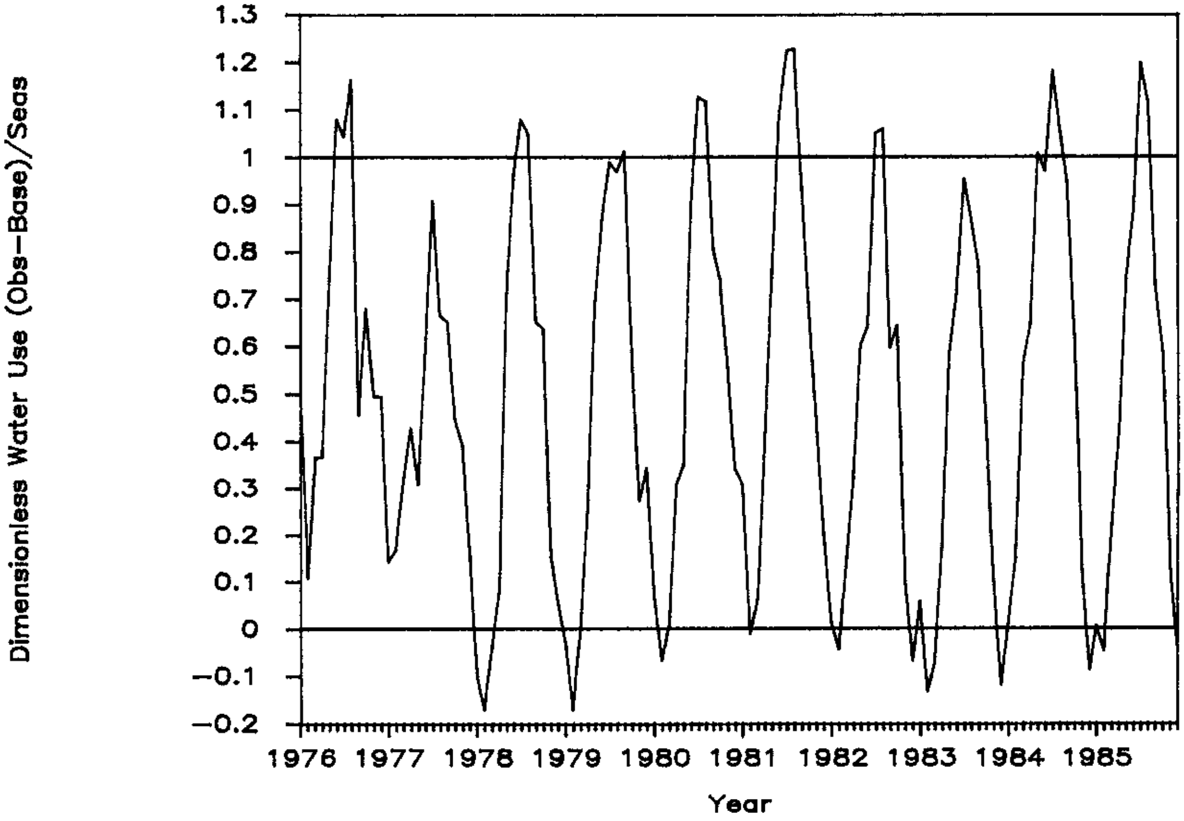
As shown in Figure [6.4 (b)] for San Diego the resulting dimensionless water use data now vary more uniformly through time from zero (minimum month) to one (maximum month) with variations caused by the prevailing weather conditions. This method of rescaling water use data is different from that normally employed in water demand studies, which is to divide the monthly water use data by the mean annual usage. The purpose of the rescaling method used here is that it accounts for variations from one community to another in both base and seasonal load characteristics instead of lumping these together as is done when

Figure 6.4

(a) Fitting trend lines to San Diego monthly water use.



(b) Dimensionless monthly water use at San Diego.



rescaling (dividing by the mean annual use). The rescaling method employed here is better able to transform the water use patterns from a number of cities in a region onto a common basis as compared with the conventional precedure.

Dimensionless water use data series are calculated similarly for all five cities and plotted on the same graph in Figure (6.5). The figure shows a remarkable convergence of the monthly time patterns in the five cities. It is apparent that demand variations with weather in each of the five cities are very closely synchronised, to the point that none of the cities consistently deviates from the average pattern even during the 1976-77 drought period. Since these cities were selected as representative of the service area, it seems likely that other cities in this area would also follow this pattern.

As a check on the representativeness of the five cities, an average curve of dimensionless water use is derived from Figure (6.5) by averaging the values of dimensionless water use for the five cities in each month, and compared in Figure (6.6) with Metropolitan monthly water deliveries rendered dimensionless by a similar method to that used in the five cities (trend lines were fitted to total water deliveries rather than to per capita usage). The dimensionless patterns of average city demand and Metropolitan deliveries are seen to be closely synchronised, with some evidence in the summer of 1981 and the winter of 1983-84 that extreme weather causes more of a swing on the Metropolitan demand pattern than on the average city pattern. Although, on average, half of the end-use demand in the cities is being met from local supplies, rather than from the Metropolitan system, it is apparent that the pattern of Metropolitan deliveries is still very

Figure 6.5 Dimensionless monthly water use in the five cities.

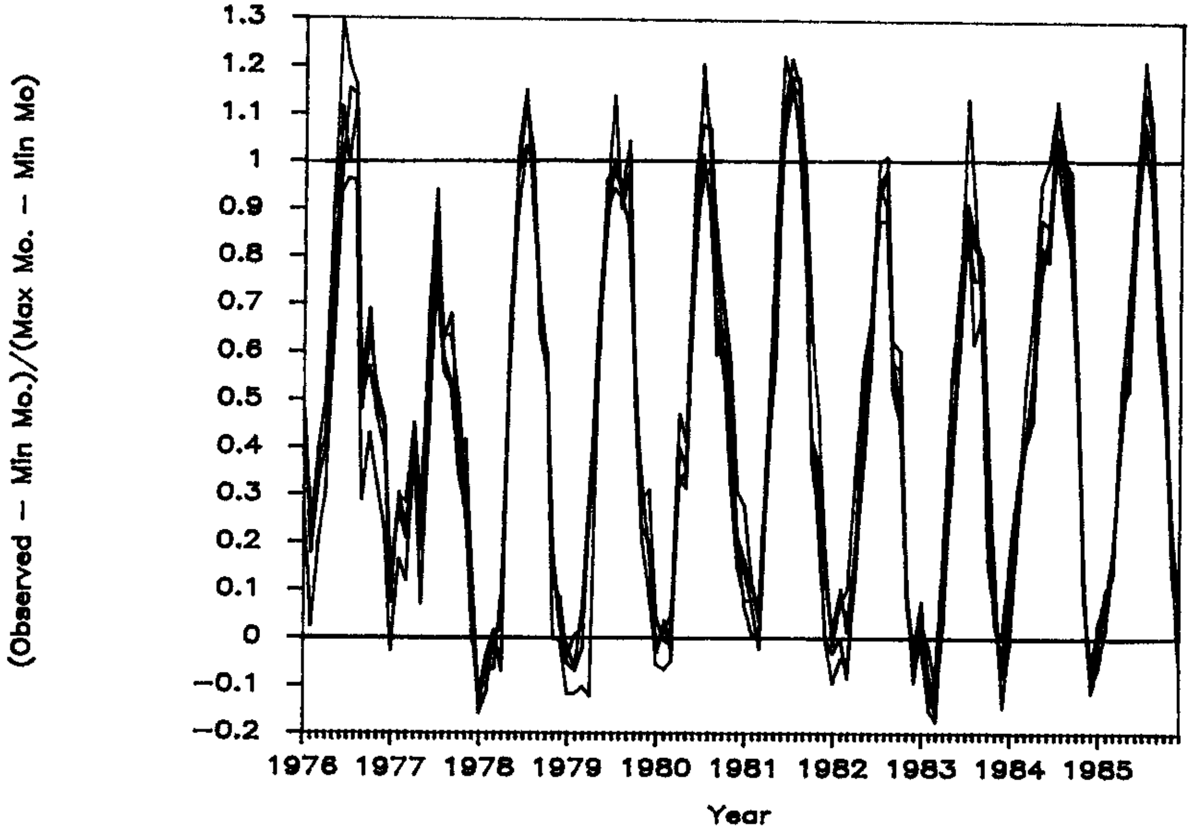


Figure 6.6 Comparison of the average curve of dimensionless water use in the five cities with dimensionless Metropolitan water deliveries.

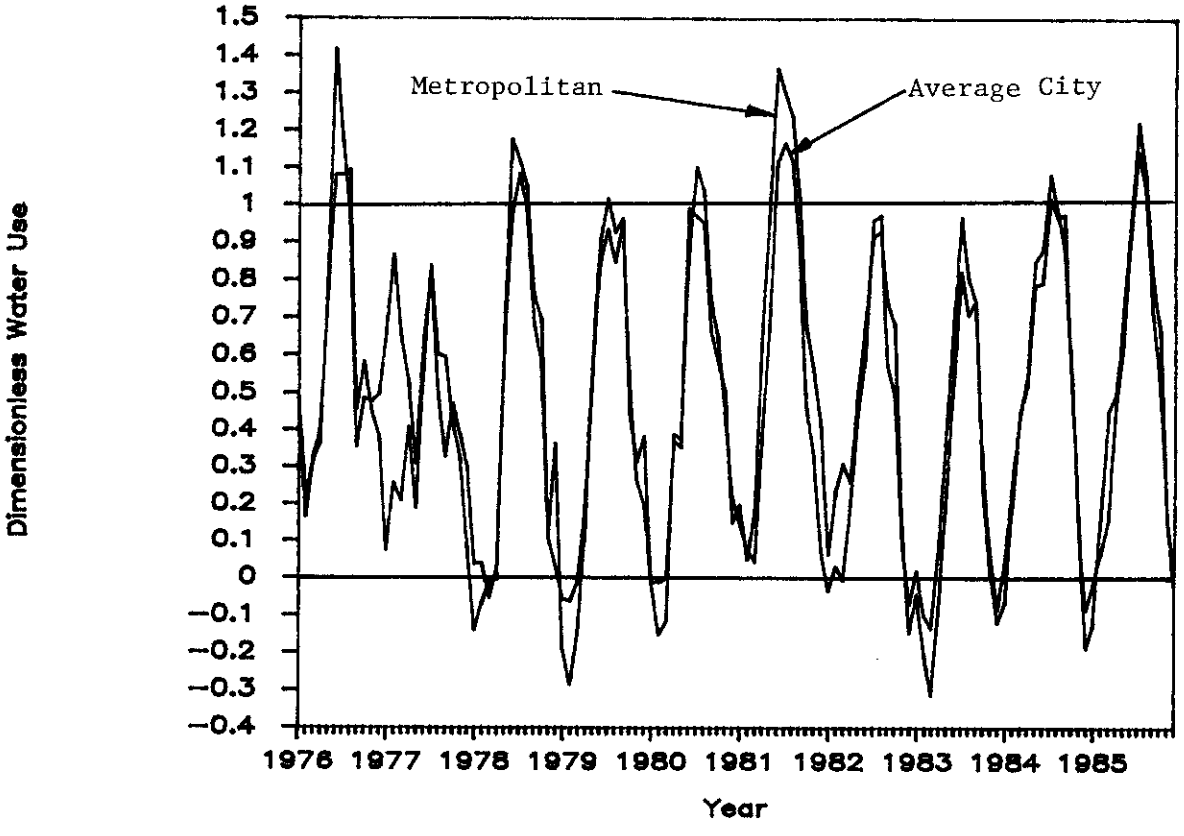


Figure 6.7 Dimensionless daily water use in the five cities for 1985.

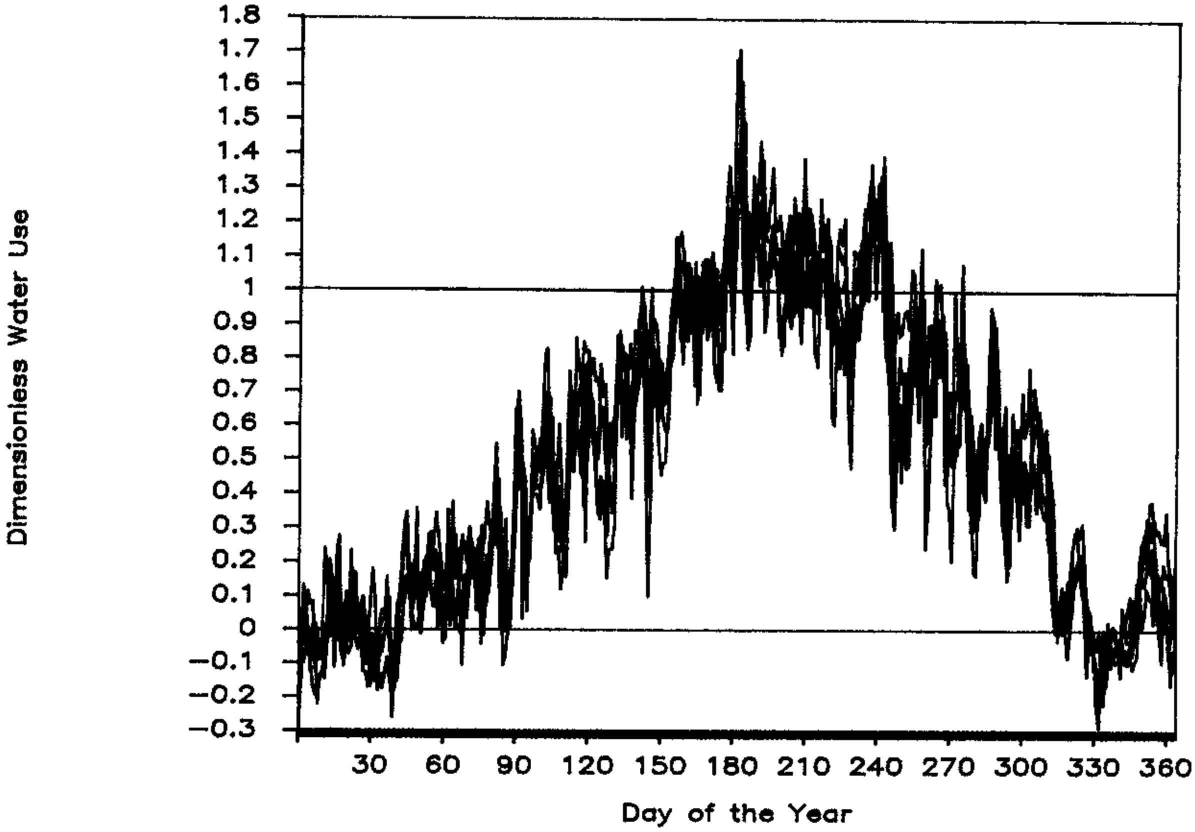
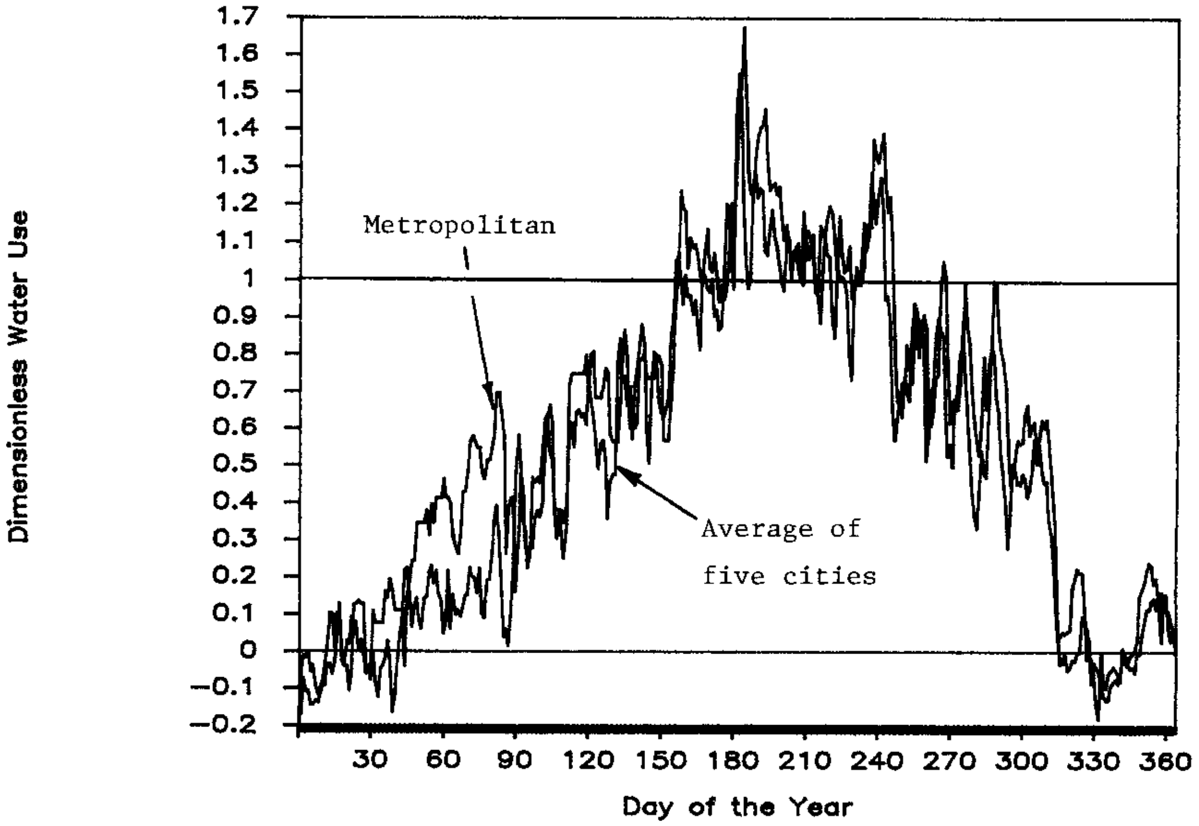


Figure 6.8 Comparison of the average dimensionless water use for the five cities with Metropolitan water deliveries for 1985.



closely tied to the pattern of end-use demands.

6.4 Daily Time Patterns

This similarity in time patterns extends to the daily data as well. In Figure (6.7) one year of data is selected from Figure (6.5), that for 1985, and "blown up" to the daily level. The daily data are rendered dimensionless using the same rescaling procedure as that for the monthly data. It is again apparent that the daily data from the five cities form a pattern that shows as much variation from day to day as from one city to another. No city stands out as consistently different from any of the others. The historic peak daily demand, recorded during a Santa Ana wind condition in the beginning of July 1985, affected all the cities in a very similar way. Likewise, near the end of the year, the effects of rainfall are seen to closely control the daily usage pattern in the five cities. This leads to the notion of a "generic city" whose time pattern represents the average of the patterns shown and which, with appropriate rescaling, could represent any of the five cities studied regardless of size or location.

Comparison of the average city daily demand with the Metropolitan delivery flows is provided for 1985 in Figure (6.8) which shows again how closely the deliveries and the end-use demands are tied together. The only significant discrepancy between them occurs in February and March 1985 when the Metropolitan system was delivering proportionately more water than the five cities demand pattern would have indicated as being necessary. It is thought that this discrepancy may have been due to additional deliveries made by Metropolitan as a consequence of the failure of the East Los Angeles feeder aqueduct at that time. The data indicate some tendency for the Metropolitan system to be a little more weather sensitive than the end-use demand pattern, presumably because during wet periods there is some greater use of local supplies while in very dry periods there is proportionately slightly less. On average, however, the two time patterns are very similar with a tendency for the deliveries to lag the changes in the end-use demands by one or two days. It would appear that this lag could be exploited to help forecast the Metropolitan deliveries one or two days ahead by using the current demands in a selected set of indicator cities, as well as temperature and rainfall information.

6.5 Per Capita Usage

Although the information presented above has been in terms of dimensionless water use, it is convenient to discuss the water use characteristics of the five cities in terms of per capita usage. Table (6.1) shows per capita usage for each of the five cities for mean annual use, base use (calculated from the fitted trend line) and seasonal use (the difference between total and base use. On average, over the 1976-1985 period, the mean annual use in the five communities was 255 gpcd with the highest use being in Las Virgenes (332 gpcd) and lowest in San Diego (194 gpcd). The overall average for the Metropolitan service area is currently estimated to be approximately 200 gpcd. It can be seen from Table (6.1) that the base use data are fairly consistent from one city to another, averaging 170 gpcd. The seasonal use data vary more from place to place, especially at Las Virgenes which has a remarkable 147 gpcd in seasonal usage alone. The

	Population	Per Capita Use (Gpcd)		
		Mean Annual	Base Vol.	Seasonal Vol.
Burbank	85,700	231	172	59
Fullerton	102,700	268	183	85
Las Virgenes	31,900	332	185	147
Riverside	171,900	251	165	86
San Diego	878,000	194	143	51
Average		255	170	85

Table 6.1 Population and per capita water use in five Southern Californian cities. The data are averages for 1976 to 1985.

	Percent of Mean Annual Use (1976-1985)		Percent of Daily Peak Use (1985 only)	
	Base	Seasonal	Base	Seasonal
Burbank	75	25	44	56
Fullerton	68	32	39	61
Las Virgenes	56	44	29	71
Riverside	66	34	34	66
San Diego	74	26	46	54
Average	67	33	38	62
MWD Deliveries	66	34	36	64

Table 6.2 Percentage of the mean annual use and peak daily water use in the base and seasonal use components. Data from the Metropolitan Water District of Southern California.

average seasonal usage volume is 85 gpcd.

The split of total usage into base and seasonal usage can also be expressed in percentage terms as shown in Table (6.2). Of the average of 255 gpcd total usage, 67% (170 gpcd) is in base use, and 33% (85 gpcd) in seasonal use. There is some variation of these figures from one city to another with the highest percentage of base use being in Burbank and the highest percentage of seasonal use being in Las Virgenes. The base/seasonal usage split can also be examined relative to the maximum daily demand. As shown in Table (6.2) for the peak daily demand in 1985, the base load comprised approximately 38% and the seasonal load 62% of the total load. Although this percentage may not be so much in favor of the seasonal load on other years (because 1985 contains the historic peak demand day), a split of 40% of the peak daily demand in the base load and 60% in the seasonal load is reasonable. The base/seasonal percentage figures calculated for the Metropolitan delivery system in Table (6.2) are nearly identical to the average values from the five cities, again indicating how closely the Metropolitan deliveries follow the end-use demands.

The principal investigator (Maidment) has conducted three previous regional studies of this type, in Texas, Florida and Pennsylvania (Maidment and Miaou, 1986). The data from Southern California are most similar to those in Texas where the percentage of peak daily demand in base and seasonal load is also approximately 40% : 60%. In Texas, however a higher proportion of the mean annual volume is in the base load (about 75%), because summer rainfall in Texas causes temporary losses in seasonal load that are not observed in Southern California where there is very little summer rainfall.

Figure 6.9 shows a schematic of the annual demand pattern with the split between base and seasonal usage noted. Effectively, 40% of the facility supply capacity in the Metropolitan service area is used for delivering the two thirds of the water in the base load, the remaining 60% of capacity being used to deliver the one third of the usage contained in the seasonal portion of the load.

The parameter values for the WATFORE model determined in this study will serve as very good initial estimates for other cities in Southern California.

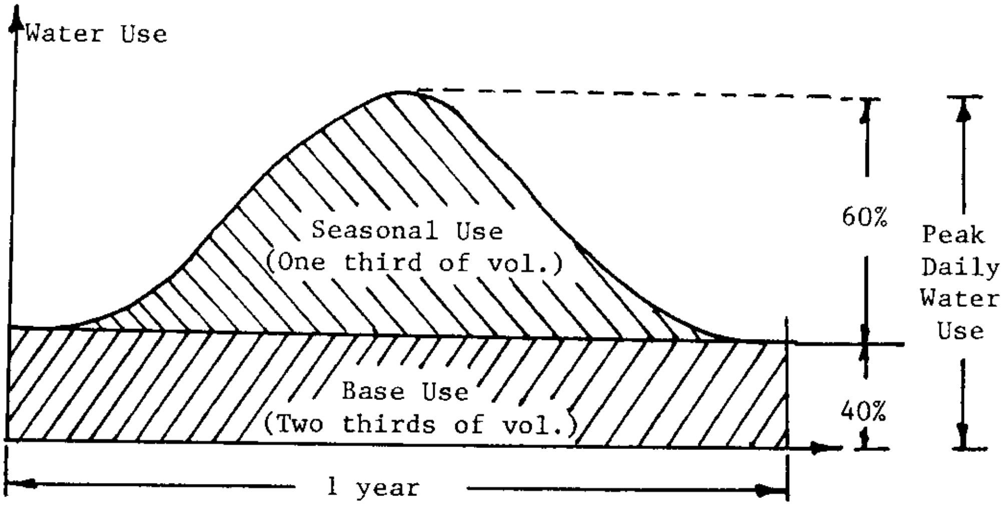


Figure 6.9 Proportion of the mean annual use volume and peak daily use rate in the base and seasonal use components. Data are average values for the five cities in Southern California computed for 1985 conditions.

7. CONCLUSIONS

(1) Methodology

a. De-seasonalization Scheme. The main methodological improvement made was to change the way of computing the seasonal water use curve related to heating conditions so that it is now calculated from a Fourier series fitted to the previous seven days maximum air temperature. The parameters of the Fourier series are then estimated by non-linear least-squares methods, along with the parameters of a rainfall response function and a lag-one autoregressive component which accounts for bias in the estimation. This automatic method replaced a laborious process of fitting a piecewise-linear function between seasonal water use and maximum air temperature during periods of no rainfall, a process that required manual screening of the data and was too subjective.

b. Calibration. A study was made to compare Kalman filtering and Box-Jenkins time series methods for model calibration and it was found that the forecast accuracy with both methods is about the same for data from Austin, Texas. Although the Kalman filter method explains more of the variation through time of the model parameters, Box-Jenkins time series methods are more robust and much easier to implement, and thus are the preferred alternative for water use data.

(2) Conservation Impact Assessment Methods

a. Methodology. Two related procedures were developed using the WATFORE model to assess the effects of conservation programs on daily water use. The first is to add intervention terms to the model to account for periods of conservation restrictions (conservation programs are represented as binary time series indicating the presence or absence of conservation). The parameters of the intervention terms are estimated along with the short-memory parameters and give a numerical estimate of the average increase or decrease in water use due to conservation. The second method consists in reconstructing daily water use patterns during a period of conservation using the WATFORE model with parameters estimated from data prior to conservation (i.e., water use is reconstructed as if no conservation had occurred). Graphically comparing reconstructed and observed water use during the period thus gives a visual indication of the effects of the conservation program.

b. Conservation Programs. Conservation programs involving water use restrictions during summer dry weather periods were implemented in Austin in 1984, 1985 and 1986 and in Corpus Christi in 1984. Voluntary conservation programs in these cities did not significantly reduce water usage. Manadatory conservation programs reduced usage proportional to the perceived severity of the program, in Austin about 10% and in Corpus Christi about 30% of peak summer usage. The effects of the severe conservation program in Corpus Christi persisted for at least a year after the program was ended. Water use restrictions in Austin were hinged around a five-day lawn watering cycle tied to the last digit of the street address (addresses ending in a specified pair of digits could water on a given day). In 1984 and 1985 in Austin, an incorrect pairing of address numbers served to induce an undersirable 5-day cycle in water use which peaked on the days when watering was allowed at addresses ending in 0 or 1 (these addresses include many commercial properties and corner lots). An address pairing scheme developed in this research, and successfully implemented by the Austin water utility in 1986, eliminated this problem by constructing address pairs that sum to 9, i.e. 0-9, 1-8, 2-7, 3-6, 4-5. Other cities using a five day watering cycle would be well advised to adopt this scheme.

(3) Regionalization

A study of time patterns of monthly and daily water use in five cities in Southern California showed that once the water use data have been made dimensionless using a method developed in this research, they follow a generic, weather-dependent pattern that is independent of city size and location in the region. This pattern exists in both the monthly and the daily data. This result is significant because it implies that there is an underlying weather-dependent mechanism influencing water use patterns throughout the region in a very similar way. The Metropolitan Water District of Southern California is sponsoring additional research following on from this project to develop a better understanding of this mechanism.

(4) Implementation

A new microcomputer package called WATCAL was developed in this project for automatic calibration of WATFORE parameters. WATCAL takes historic data on water use, rainfall and maximum air temperature and determines a configuration file of parameter values for the given city. One to three years of daily data and five to ten years of monthly data are required for this purpose. The configuration file is passed to WATFORE where it is used with current data on water use and the weather variables to make water use forecasts. In the short term, it is usually assumed that there is no rainfall, and air temperature is as forecast by the National Weather Service. For longer term forecasts of several weeks or months ahead, historic weather sequences are employed to produce forecasts of water use which are conditioned on these sequences.

In WATCAL, trend lines are fitted to weather-corrected values of the base use (minimum month) and maximum seasonal use (difference between minimum and maximum month), then the daily water use data are rendered dimensionless by subtracting the base use and dividing the result by the maximum seasonal use. In this way, the bulk of the model parameters are produced in a form made dimensionless in water use that permits parameter values determined for one city in a region to be used as very good initial estimates of the parameter values in a nearby city.

Both WATFORE and WATCAL are menu-driven IBM-PC based packages that have their own data management and graphics routines so that they can operate in a stand-alone manner. The software packages WATFORE and WATCAL are being used by water utilities in Austin and Longview, Texas, and by the Metropolitan Water District of Southern California. The Metropolitan Water District has calibrated WATFORE to forecast flows in their regional delivery system taking water from long distance water transfers from northern California and the Colorado River, and they are seeking to implement WATFORE and WATCAL in their 27 member agencies which collectively serve 135 cities and water districts containing 13 million people in Southern California.

Acknowledgements

The authors would like to thank Dr. Shaw-Pin Miaou for his valuable assistance in reviewing this document, and whose doctoral research made up much of the first year of this project; to Dr Wayne Jordan and Ms. Ellen Wadsworth for their careful reviews of the manuscript; and to the staff at The Center for Research in Water Resources, University of Texas at Austin.

The assistance of the following water utility personnel in Texas is greatly appreciated: Mr. Michael Erdmann, Project Manager, Water and Wastewater Department, and Ms. Faith M. George, Manager, Water Resource Management Division, Resource Management Department, City of Austin, Texas; Mr. Hubert Hall, Production Superintendent, Department of Public Utilities, Water Division, City of Corpus Christi, Texas; Mr. W.A. Johnson, City Engineer, and Mr. Kenneth Gill, Engineer, City of Longview, Texas.

The research reported here on Southern California cities was supported by the Metropolitan Water District of Southern California. These results of are included in this report because the research benefited from and contributed to the parallel effort supported by the Texas Water Resources Institute. The advice and assistance of the following personnel of the Metropolitan Water District is appreciated: Don Adams, Jeff Davis, Kris Helm, Dr Wiley Horne, Paul Teigen and Charles Voyles.

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APPENDIX A

DAILY WATER USE, TEMPERATURE, RAINFALL DATA

Austin, Texas 1984-1985

Austin, Texas - 1984

Date	Water Use (MGD)	Rainfall (INCHES)	Max. Temp. (F)
1/ 1	79.73	.01	60
1/ 2	77.46	.04	54
1/ 3	73.34	0	57
1/ 4	76.78	0	74
1/ 5	75.16	0	70
1/ 6	71.44	0	75
1/ 7	75.25	0	65
1/ 8	70.97	.98	64
1/ 9	67.54	.4	65
1/10	68.82	0	48
1/11	72.59	0	49
1/12	70.89	0	61
1/13	70	0	45
1/14	70.22	.01	35
1/15	70.29	0	39
1/16	71.29	0	40
1/17	69.68	0	43
1/18	72.4	0	40
1/19	79.1	0	37
1/20	76.84	0	33
1/21	77.92	0	44
1/22	71.95	.22	45
1/23	70.71	0	63
1/24	67.31	0	49
1/25	68.77	0	63
1/26	69.46	0	68
1/27	71.04	0	67
1/28	71.42	0	78
1/29	71.31	0	77
1/30	69.46	0	61
1/31	68.5	0	54
2/ 1	69.39	0	62
2/ 2	65.29	.06	65
2/ 3	68.3	0	68
2/ 4	71.6	0	69
2/ 5	69.61	0	68
2/ 6	71.43	0	54
2/ 7	68.98	0	64
2/ 8	66.23	.07	56
2/ 9	67.31	.05	72
2/10	69.12	0	77
2/11	68	0	75
2/12	67.25	.07	70
2/13	69.75	0	79
2/14	69.42	0	79
2/15	69.57	0	82
2/16	75.88	0	74
2/17	70.5	0	78
2/18	72.73	.04	75

2/19	65.16	0	54
2/20	64.94	.23	49
2/21	68.64	0	63
2/22	71.39	0	73
2/23	74.44	0	77
2/24	75.18	0	70
2/25	74.29	0	75
2/26	67.9	.48	72
2/27	66.53	0	56
2/28	67.99	0	54
3/ 1	72.43	0	67
3/ 2	76.31	0	79
3/ 3	77.16	0	76
3/ 4	73.87	.41	79
3/ 5	67.77	.01	52
3/ 6	70.06	0	58
3/ 7	71.57	0	71
3/ 8	77.73	0	76
3/ 9	77.08	0	72
3/10	74.96	0	67
3/11	64.13	.04	64
3/12	71.46	1.23	85
3/13	71.93	0	82
3/14	70.3	0	73
3/15	64.37	.05	76
3/16	72.68	.01	79
3/17	71.5	0	80
3/18	73.32	.24	83
3/19	71.28	0	67
3/20	75.64	0	74
3/21	80.23	0	77
3/22	74.98	0	78
3/23	68.68	.43	81
3/24	72.14	.05	74
3/25	76.37	0	78
3/26	77.54	0	84
3/27	83.75	0	96
3/28	75.56	0	70
3/29	86.36	0	71
3/30	77.52	.02	71
3/31	83.88	0	75
4/ 1	77.2	0	72
4/ 2	76.38	.03	83
4/ 3	84.84	0	79
4/ 4	85.27	0	74
4/ 5	91.09	0	74
4/ 6	85.6	0	74
4/ 7	75.94	.02	74
4/ 8	90.37	0	82
4/ 9	96.72	0	90
4/10	98.25	0	89
4/11	105.23	0	87
4/12	102.57	0	82

4/13	108.65	0	90
4/14	108.92	0	81
4/15	102.62	0	76
4/16	102.1	0	79
4/17	113.65	0	86
4/18	106.26	0	89
4/19	115.64	0	97
4/20	117.9	0	94
4/21	128.39	0	90
4/22	108.1	0	81
4/23	118.41	0	85
4/24	120.67	0	90
4/25	105.48	0	82
4/26	118.55	.01	96
4/27	124.55	0	88
4/28	121.18	0	87
4/29	113.6	0	93
4/30	111.52	0	78
5/ 1	88.25	.02	85
5/ 2	98.59	.02	88
5/ 3	125.37	0	95
5/ 4	133.58	0	100
5/ 5	139.85	0	100
5/ 6	136.18	0	99
5/ 7	120.32	0	97
5/ 8	124.23	0	82
5/ 9	131.46	0	86
5/10	129.84	0	88
5/11	130.14	0	92
5/12	140.32	0	93
5/13	133.36	0	93
5/14	132.83	0	92
5/15	128.19	0	87
5/16	101.63	.21	83
5/17	89.06	.35	87
5/18	74.68	.13	77
5/19	74.47	.54	84
5/20	77.54	0	88
5/21	86.82	0	93
5/22	93.15	0	93
5/23	100.99	0	92
5/24	109.58	0	92
5/25	112.62	0	93
5/26	116.66	0	95
5/27	118.34	0	96
5/28	105.02	0	90
5/29	104.96	0	80
5/30	114.03	0	80
5/31	120.96	0	86
6/ 1	128.25	0	88
6/ 2	135.37	0	90
6/ 3	139.52	0	91
6/ 4	104.59	.22	88

6/ 5	85.21	.64	91
6/ 6	82.75	.34	95
6/ 7	85.1	0	91
6/ 8	90.57	0	92
6/ 9	95.55	.01	92
6/10	104.48	0	92
6/11	112.67	0	92
6/12	99.09	.28	89
6/13	85.19	.05	91
6/14	95.45	0	92
6/15	104.98	0	93
6/16	112.92	0	93
6/17	117.48	0	95
6/18	125.75	0	95
6/19	117.27	.12	90
6/20	118.29	0	96
6/21	136.65	0	96
6/22	139.07	0	97
6/23	144.14	0	97
6/24	141.99	0	100
6/25	144.29	0	102
6/26	152.24	0	102
6/27	146.79	0	103
6/28	106.87	.01	88
6/29	116.66	0	95
6/30	136.2	0	98
7/ 1	137.79	0	98
7/ 2	139.76	0	98
7/ 3	137.41	0	97
7/ 4	137.37	0	98
7/ 5	137.46	0	98
7/ 6	150.04	0	100
7/ 7	152.09	0	99
7/ 8	150.77	0	99
7/ 9	148.58	0	98
7/10	148.69	0	99
7/11	147.84	0	100
7/12	143.12	0	98
7/13	142.3	0	98
7/14	136.9	0	99
7/15	137.48	0	99
7/16	139.22	0	101
7/17	139.87	0	105
7/18	123.26	.38	98
7/19	114.3	0	99
7/20	118.3	0	99
7/21	140.37	0	96
7/22	134.82	0	97
7/23	134.59	0	99
7/24	89.77	.75	83
7/25	85.18	0	89
7/26	102.39	0	95
7/27	96.6	.04	93

7/28	100.18	0	93
7/29	101.16	0	92
7/30	108.73	0	91
7/31	127.07	0	95
8/ 1	126.37	0	95
8/ 2	124.45	0	95
8/ 3	118.57	0	96
8/ 4	112.54	0	96
8/ 5	128.72	0	97
8/ 6	122.69	0	98
8/ 7	123.33	0	99
8/ 8	120.12	0	99
8/ 9	119.55	0	98
8/10	138.64	0	99
8/11	133.14	0	97
8/12	109.64	.07	94
8/13	101.41	0	94
8/14	100.87	.01	97
8/15	98.74	.03	95
8/16	111.82	0	95
8/17	120.34	0	99
8/18	132.1	0	103
8/19	140.5	0	106
8/20	152.3	0	103
8/21	151.45	0	100
8/22	146.82	0	99
8/23	149.42	0	101
8/24	145.69	0	102
8/25	153.33	0	96
8/26	146.19	0	98
8/27	146.32	0	100
8/28	143.43	0	100
8/29	142.76	0	100
8/30	153.07	0	99
8/31	131.87	.34	95
9/ 1	98.64	.02	95
9/ 2	93.2	0	90
9/ 3	92.86	.6	91
9/ 4	87.27	0	88
9/ 5	95.67	0	91
9/ 6	105.34	0	90
9/ 7	107.66	0	90
9/ 8	113.11	0	93
9/ 9	135.28	0	95
9/10	130.18	0	94
9/11	130.61	0	95
9/12	129.49	0	94
9/13	128	0	93
9/14	134.58	0	94
9/15	135.01	0	87
9/16	132.05	0	85
9/17	128.16	0	88
9/18	130.51	0	89

9/19	137.55	0	85
9/20	110.05	0	80
9/21	87.28	0	76
9/22	97.63	0	88
9/23	110.6	0	91
9/24	123.38	0	93
9/25	115.27	.01	88
9/26	106.4	0	74
9/27	109.6	0	80
9/28	87.93	0	65
9/29	94.85	0	62
9/30	115.44	0	70
10/ 1	115.2	0	76
10/ 2	115.34	0	80
10/ 3	111.02	0	81
10/ 4	105.31	.02	79
10/ 5	106.01	0	91
10/ 6	116.35	.01	91
10/ 7	84.05	1.79	78
10/ 8	85.5	0	85
10/ 9	81.43	.02	81
10/10	84.51	.73	83
10/11	79.22	1.29	72
10/12	80.84	.04	84
10/13	76.76	1.49	72
10/14	76.68	.79	79
10/15	81.61	0	88
10/16	81.4	0	89
10/17	79.4	0	80
10/18	85.09	.05	88
10/19	81.95	0	79
10/20	77.5	1.02	84
10/21	78.68	1.73	66
10/22	76.59	.14	60
10/23	75.25	.39	59
10/24	74.17	.24	59
10/25	74.54	.11	64
10/26	75.28	.26	78
10/27	76.45	.17	76
10/28	81.09	.05	83
10/29	76.25	0	81
10/30	77.64	0	81
10/31	78.79	0	85
11/ 1	77.2	.07	83
11/ 2	72.54	0	59
11/ 3	73.34	0	59
11/ 4	75.89	0	76
11/ 5	80.06	0	73
11/ 6	78.04	0	72
11/ 7	79.77	0	77
11/ 8	79.28	0	83
11/ 9	81.92	0	82
11/10	80.04	0	73

11/11	81.19	0	67
11/12	84.44	0	71
11/13	81.19	0	72
11/14	83.77	0	79
11/15	84	0	80
11/16	80.63	0	68
11/17	79.03	.05	69
11/18	75.19	.49	70
11/19	76.22	0	54
11/20	76.09	0	47
11/21	77.53	0	55
11/22	65.65	0	54
11/23	67.83	0	57
11/24	70.45	1.26	68
11/25	72.04	0	73
11/26	76.74	.01	74
11/27	75.71	0	58
11/28	76.21	0	61
11/29	78.08	0	73
11/30	74.82	0	68
12/ 1	76.76	0	72
12/ 2	73.32	0	71
12/ 3	75.2	.07	56
12/ 4	71.94	.25	47
12/ 5	76.52	.03	48
12/ 6	73.4	0	50
12/ 7	76.79	0	58
12/ 8	75.38	0	66
12/ 9	77.19	0	75
12/10	75.71	0	75
12/11	78.14	0	74
12/12	77.64	0	71
12/13	67.66	.22	77
12/14	73.94	.07	70
12/15	73.79	1.36	75
12/16	72.92	.1	62
12/17	72.1	.13	70
12/18	73.18	0	71
12/19	73.05	0	73
12/20	74.22	0	76
12/21	73.25	0	79
12/22	65.45	0	62
12/23	63.27	0	63
12/24	63.03	0	75
12/25	55.04	0	44
12/26	65.87	.01	58
12/27	68.19	.19	68
12/28	69.8	0	76
12/29	66.36	.03	75
12/30	66.05	0	77
12/31	68.69	.77	72

Austin, Texas - 1985

Date	Water Use (MGD)	Rainfall (INCHES)	Max. Temp. (F)
1/ 1	65.398	.05	49
1/ 2	76.062	.34	32
1/ 3	84.98	0	50
1/ 4	79.252	0	56
1/ 5	72.9	0	56
1/ 6	72.726	0	62
1/ 7	73.255	0	61
1/ 8	69.963	0	60
1/ 9	73.884	0	69
1/10	71.451	0	56
1/11	71.466	0	40
1/12	76.805	.26	32
1/13	84.234	.08	34
1/14	81.376	0	55
1/15	77.624	0	52
1/16	73.197	.48	52
1/17	75.308	0	57
1/18	76.15	0	63
1/19	78.196	0	70
1/20	82.027	0	34
1/21	89.783	.08	42
1/22	84.669	.04	42
1/23	78.22	0	46
1/24	78.705	0	63
1/25	78.889	0	74
1/26	73.433	.08	51
1/27	76.545	.04	75
1/28	76.742	0	53
1/29	79.759	0	53
1/30	77.641	.01	71
1/31	82.128	0	47
2/ 1	89.879	.27	23
2/ 2	97.916	0	30
2/ 3	101.34	0	32
2/ 4	101.637	.06	36
2/ 5	88.219	0	42
2/ 6	86.414	0	45
2/ 7	82.225	0	49
2/ 8	77.939	0	56
2/ 9	75.532	0	70
2/10	74.415	.13	73
2/11	76.102	0	55
2/12	77.871	0	64
2/13	78.168	0	66
2/14	74.207	0	59
2/15	74.832	0	57
2/16	77.401	0	72
2/17	76.982	0	69

2/18	76.495	0	68
2/19	78.539	0	72
2/20	76.964	0	67
2/21	77.511	.01	72
2/22	76.108	.29	74
2/23	71.887	.71	73
2/24	69.979	0	58
2/25	75.621	0	69
2/26	75.532	.08	68
2/27	74.116	0	59
2/28	72.19	.55	57
3/ 1	76.418	0	79
3/ 2	73.841	0	74
3/ 3	74.898	0	78
3/ 4	78.674	.05	73
3/ 5	75.047	0	63
3/ 6	77.276	0	67
3/ 7	78.491	0	78
3/ 8	80.424	0	77
3/ 9	84.123	0	79
3/10	80.392	0	78
3/11	85.475	0	84
3/12	76.689	.01	74
3/13	82.32	0	81
3/14	71.433	.53	57
3/15	70.372	.15	54
3/16	71.063	0	58
3/17	72.341	0	65
3/18	76.681	0	69
3/19	73.997	.05	67
3/20	73.594	.85	75
3/21	73.335	0	62
3/22	76.287	0	72
3/23	79.876	0	75
3/24	84.239	0	81
3/25	87.912	0	81
3/26	82.3	.08	75
3/27	77.847	.07	80
3/28	81.048	0	80
3/29	78.28	0	75
3/30	80.945	.05	73
3/31	86.473	0	70
4/ 1	84.831	0	78
4/ 2	89.098	0	80
4/ 3	96.099	0	83
4/ 4	93.226	0	79
4/ 5	99.637	0	76
4/ 6	101.718	0	82
4/ 7	81.247	0	74
4/ 8	78.866	0	62
4/ 9	90.369	0	74
4/10	79.931	.17	63
4/11	78.618	.32	70

4/12	81.471	0	78
4/13	81.444	.65	77
4/14	80.935	0	81
4/15	84.393	0	90
4/16	91.638	0	87
4/17	91.376	0	84
4/18	100.042	0	83
4/19	85.617	0	76
4/20	91.775	0	83
4/21	83.843	.27	78
4/22	84.138	.24	84
4/23	90.439	0	87
4/24	90.916	0	81
4/25	89.933	.45	83
4/26	82.559	.01	83
4/27	86.008	0	83
4/28	79.259	.01	82
4/29	82.39	.11	83
4/30	85.574	.37	85
5/ 1	84.954	0	84
5/ 2	91.2	0	82
5/ 3	97.958	0	82
5/ 4	101.742	0	82
5/ 5	101.888	0	83
5/ 6	111.369	0	84
5/ 7	113.11	0	87
5/ 8	99.529	.1	90
5/ 9	110.021	0	85
5/10	110.916	0	88
5/11	111.111	0	88
5/12	107.064	0	84
5/13	96.034	1.22	84
5/14	85.124	.27	82
5/15	87.194	0	83
5/16	91.894	0	88
5/17	88.646	.27	82
5/18	91.578	0	80
5/19	95.24	0	86
5/20	98.404	0	85
5/21	89.386	.47	89
5/22	84.407	.11	80
5/23	89.521	0	86
5/24	92.616	0	85
5/25	98.277	0	90
5/26	104.531	0	89
5/27	107.201	0	88
5/28	103.23	0	88
5/29	113.748	0	93
5/30	125.313	0	97
5/31	130.56	0	95
6/ 1	137.645	0	94
6/ 2	134.902	0	93
6/ 3	129.929	0	93

6/ 4	133.887	0	93
6/ 5	110.475	1.08	88
6/ 6	87.555	.94	85
6/ 7	91.401	0	92
6/ 8	95.188	0	96
6/ 9	91.936	0	94
6/10	108.429	0	93
6/11	108.012	.03	92
6/12	103.453	0	84
6/13	114.73	0	84
6/14	113.039	0	90
6/15	124.724	0	93
6/16	125.804	0	94
6/17	125.757	0	95
6/18	113.625	.27	91
6/19	97.97	0	84
6/20	112.104	0	87
6/21	107.176	.02	89
6/22	87.88	2.53	79
6/23	87.127	.08	87
6/24	89.999	.01	90
6/25	96.753	.15	89
6/26	98.352	0	90
6/27	100.248	0	89
6/28	109.933	0	86
6/29	116.392	0	89
6/30	122.592	0	90
7/ 1	127.695	0	91
7/ 2	121.045	.2	92
7/ 3	98.881	.21	86
7/ 4	82.644	1.11	79
7/ 5	94.487	0	88
7/ 6	93.277	0	93
7/ 7	99.811	0	92
7/ 8	105.455	0	90
7/ 9	110.953	0	91
7/10	119.195	0	92
7/11	119.502	0	89
7/12	114.055	.28	90
7/13	119.054	0	92
7/14	119.723	0	92
7/15	129.206	0	92
7/16	133.148	0	95
7/17	141.574	0	95
7/18	135.778	0	95
7/19	130.705	0	93
7/20	124.081	0	93
7/21	134.274	0	94
7/22	143.206	0	96
7/23	147.266	0	96
7/24	149.144	0	96
7/25	153.571	0	97
7/26	156.34	0	97

7/27	153.393	0	98
7/28	155.288	0	99
7/29	160.662	0	97
7/30	163.596	0	96
7/31	143.888	0	97
8/ 1	144.289	0	98
8/ 2	141.067	0	100
8/ 3	150.87	0	98
8/ 4	157.637	0	99
8/ 5	158.559	0	100
8/ 6	159.353	0	100
8/ 7	148.643	0	101
8/ 8	160.988	0	100
8/ 9	168.221	0	100
8/10	161.863	0	99
8/11	155.967	0	100
8/12	149.926	0	97
8/13	146.466	0	97
8/14	158.031	0	97
8/15	144.294	.06	97
8/16	140.043	0	101
8/17	136.575	0	100
8/18	145.628	0	102
8/19	165.344	0	102
8/20	165.871	0	102
8/21	162.879	0	100
8/22	148.247	0	98
8/23	150.156	0	99
8/24	141.559	0	100
8/25	136.708	0	96
8/26	148.313	0	101
8/27	146.393	0	94
8/28	149.753	0	95
8/29	147.479	.22	91
8/30	139.171	0	96
8/31	137.987	0	101
9/ 1	134.429	0	104
9/ 2	156.079	0	101
9/ 3	157.3	0	103
9/ 4	151.784	0	99
9/ 5	131.749	.3	96
9/ 6	103.565	.69	92
9/ 7	115.574	0	97
9/ 8	124.781	0	97
9/ 9	129.911	0	96
9/10	111.513	.13	94
9/11	102.74	.15	80
9/12	101.35	0	84
9/13	109.168	0	89
9/14	101.483	.96	87
9/15	100.039	0	83
9/16	100.361	0	87
9/17	100.972	0	90

9/18	110.323	0	92
9/19	112.692	0	90
9/20	114.245	0	89
9/21	119.34	0	89
9/22	126.247	0	91
9/23	121.379	0	87
9/24	120.739	0	86
9/25	115.228	.08	94
9/26	113.506	0	80
9/27	116.896	0	86
9/28	98.927	.23	73
9/29	90.86	1.61	75
9/30	91.68	0	65
10/ 1	88.155	0	71
10/ 2	90.107	0	75
10/ 3	95.396	0	83
10/ 4	94.522	0	82
10/ 5	95.856	0	76
10/ 6	101.437	0	79
10/ 7	98.873	0	83
10/ 8	110.846	0	88
10/ 9	98.23	0	86
10/10	95.172	0	88
10/11	99.474	0	89
10/12	106.058	0	89
10/13	106.366	0	92
10/14	98.226	2.98	90
10/15	85.173	.67	71
10/16	82.894	0	76
10/17	83.891	.14	82
10/18	85.915	.07	87
10/19	81.153	1.66	76
10/20	81.21	0	75
10/21	82.404	.22	70
10/22	83.857	.02	79
10/23	83.384	0	84
10/24	81.988	0	85
10/25	83.925	0	83
10/26	82.713	0	79
10/27	83.45	0	79
10/28	83.871	0	74
10/29	80.927	.08	66
10/30	81.324	0	69
10/31	85.882	0	75
11/ 1	82.846	.47	63
11/ 2	81.33	.15	61
11/ 3	84.997	0	72
11/ 4	84.893	0	72
11/ 5	83.645	0	74
11/ 6	83.411	0	80
11/ 7	83.75	0	70
11/ 8	83.782	0	80
11/ 9	86.544	0	81

11/10	88.49	.06	84
11/11	80.143	.11	73
11/12	84.447	.01	82
11/13	84.514	0	82
11/14	86.999	0	82
11/15	81.311	.24	73
11/16	77.28	.21	55
11/17	80.622	.06	72
11/18	84.989	0	81
11/19	84.574	.45	80
11/20	82.273	0	53
11/21	83.69	0	60
11/22	83.156	0	67
11/23	77.696	.23	70
11/24	78.124	1.05	68
11/25	82.358	.17	80
11/26	79.78	.13	77
11/27	76.537	1.39	63
11/28	70.111	0	50
11/29	68.468	0	54
11/30	73.622	.02	78
12/ 1	73.816	0	68
12/ 2	83.735	0	42
12/ 3	81.769	0	47
12/ 4	80.822	.02	68
12/ 5	83.458	0	63
12/ 6	78.932	0	65
12/ 7	78.564	0	67
12/ 8	84.932	0	76
12/ 9	80.862	0	78
12/10	78.817	.92	73
12/11	79.918	.11	42
12/12	81.602	.01	37
12/13	83.663	0	42
12/14	86.678	0	46
12/15	81.732	0	54
12/16	82.587	0	62
12/17	78.599	0	58
12/18	79.699	0	60
12/19	76.513	0	56
12/20	80.857	0	58
12/21	76.412	0	66
12/22	72.734	0	71
12/23	78.612	0	70
12/24	74.895	0	61
12/25	64.924	0	47
12/26	75.338	0	55
12/27	73.209	0	65
12/28	72.322	0	62
12/29	72.417	0	65
12/30	74.162	0	70
12/31	77.147	0	61

APPENDIX B

DAILY WATER USE, RAINFALL, TEMPERATURE DATA

Corpus Christi, Texas 1984-1985

Corpus Christi, Texas - 1984

Date	Water Use (MGD)	Rainfall (INCHES)	Max. Temp. (F)
1/1	78.76	0	70
1/2	72.94	0	70
1/3	63.18	0	62
1/4	74.08	0	70
1/5	76.17	0	75
1/6	68.96	0	78
1/7	71.16	0	68
1/8	68.56	.55	69
1/9	61.88	2.89	71
1/10	59.86	0	59
1/11	72.12	0	48
1/12	65.15	0	66
1/13	66.03	0	53
1/14	59.85	.15	46
1/15	63.02	0	44
1/16	68.03	0	47
1/17	63.68	0	45
1/18	73.23	.2	46
1/19	78.2	0	39
1/20	75.48	.02	37
1/21	77.02	0	44
1/22	70	.15	54
1/23	66.47	.1	55
1/24	65.72	.61	57
1/25	64.99	.89	59
1/26	68.26	0	64
1/27	68.02	0	68
1/28	69.82	0	73
1/29	63.34	0	76
1/30	67.63	.02	60
1/31	68.66	.33	49
2/1	62.1	0	55
2/2	68.07	.12	63
2/3	68.56	0	65
2/4	68.79	0	68
2/5	69.67	0	67
2/6	69.1	0	54
2/7	65.21	0	63
2/8	67.68	0	69
2/9	65.48	0	80
2/10	70.62	0	78
2/11	62.42	0	77
2/12	56.68	0	77
2/13	76.05	0	80
2/14	71.71	0	77
2/15	72.03	0	82
2/16	74.77	0	78
2/17	68.62	0	79
2/18	70.17	0	75

2/19	62.95	.04	64
2/20	60.64	.23	52
2/21	65.05	0	63
2/22	65.96	0	74
2/23	67.46	0	74
2/24	71.71	0	75
2/25	70.5	0	77
2/26	72.83	0	82
2/27	67.72	0	63
2/28	71.81	0	61
2/29	73.13	0	56
3/1	70.64	0	65
3/2	73.47	0	82
3/3	73.84	0	75
3/4	71.33	.07	75
3/5	68.95	0	67
3/6	71.45	0	64
3/7	72.72	0	73
3/8	73.72	0	75
3/9	71.26	0	75
3/10	73.43	.01	70
3/11	70.11	0	75
3/12	71.14	.02	85
3/13	71.27	0	82
3/14	73.46	0	76
3/15	75.04	0	83
3/16	72.61	0	82
3/17	76.13	0	76
3/18	76.9	0	81
3/19	71.52	.08	73
3/20	71.4	0	76
3/21	74.14	0	77
3/22	76.79	0	78
3/23	75.62	0	80
3/24	78.05	.01	77
3/25	78.9	0	79
3/26	82.45	0	88
3/27	79.4	0	101
3/28	82.2	0	78
3/29	82.24	0	74
3/30	78.59	0	70
3/31	74.13	0	73
4/1	78.31	0	74
4/2	74.35	0	86
4/3	80.89	0	89
4/4	87.1	0	79
4/5	80.88	0	69
4/6	78.61	0	75
4/7	76.51	0	75
4/8	78.6	0	87
4/9	88.45	0	90
4/10	79.41	0	92
4/11	84.16	0	86

4/12	85.15	0	83
4/13	87.61	0	84
4/14	78.81	0	85
4/15	90.44	0	82
4/16	88.71	0	80
4/17	85.35	0	90
4/18	82.87	0	91
4/19	97.53	0	94
4/20	92.04	0	89
4/21	101.61	0	92
4/22	92.88	0	80
4/23	95.14	0	83
4/24	97.77	0	85
4/25	96.19	0	83
4/26	94.51	0	102
4/27	95.67	0	88
4/28	92.72	0	84
4/29	87.7	0	91
4/30	85.76	0	76
5/1	86.05	0	85
5/2	92.84	0	88
5/3	102.15	0	103
5/4	101.6	0	93
5/5	103.09	0	87
5/6	101.18	0	92
5/7	100.24	.14	90
5/8	94.19	.01	81
5/9	82.28	0	80
5/10	92.69	0	81
5/11	91.84	0	86
5/12	96.43	0	87
5/13	99.5	0	85
5/14	98.15	0	84
5/15	92.07	0	83
5/16	86.96	.18	79
5/17	71.91	.43	78
5/18	68.32	1.45	81
5/19	83.02	.01	87
5/20	71.09	0	94
5/21	81.23	0	90
5/22	82.34	0	88
5/23	79.84	0	87
5/24	85.35	0	88
5/25	83.69	0	89
5/26	87.81	0	88
5/27	84.3	0	89
5/28	90.06	0	89
5/29	84.26	0	84
5/30	85.36	0	78
5/31	86.65	0	80
6/1	87.92	0	83
6/2	89.28	0	85
6/3	87.72	0	87

6/4	87.63	.06	87
6/5	85.29	0	87
6/6	81.93	0	90
6/7	88.63	0	90
6/8	88.8	0	89
6/9	86.23	.05	89
6/10	86.7	.02	87
6/11	85.31	0	90
6/12	83.22	0	90
6/13	85.47	0	89
6/14	85.78	0	88
6/15	83.05	0	90
6/16	90.67	0	91
6/17	82.37	.06	91
6/18	90.52	.03	91
6/19	91.66	0	91
6/20	85.22	0	93
6/21	87.5	0	93
6/22	89.13	0	93
6/23	91.29	0	95
6/24	92	0	94
6/25	99.85	0	96
6/26	96.62	0	94
6/27	91.95	0	95
6/28	93.42	0	93
6/29	103.93	0	95
6/30	105.73	.01	96
7/1	86.68	.13	96
7/2	72.85	0	94
7/3	70.61	0	93
7/4	72.02	0	94
7/5	75.02	0	94
7/6	74.26	0	93
7/7	71.27	0	94
7/8	65.92	0	94
7/9	78.01	0	94
7/10	76.3	0	94
7/11	67.75	0	94
7/12	89.21	0	93
7/13	71.27	0	93
7/14	61.57	0	93
7/15	71.43	0	91
7/16	71.74	0	95
7/17	70.34	0	99
7/18	67.44	0	92
7/19	68.13	0	95
7/20	75.92	0	93
7/21	66.77	0	93
7/22	62.57	0	94
7/23	67.66	0	94
7/24	68.09	0	94
7/25	66.37	0	90
7/26	65.17	0	95

7/27	68.23	0	94
7/28	60.53	.12	87
7/29	60.76	0	94
7/30	65.22	0	92
7/31	61	0	93
8/1	65.01	0	94
8/2	60.9	0	93
8/3	64.43	0	94
8/4	57.98	.71	86
8/5	54.18	0	94
8/6	60.59	0	94
8/7	62.92	0	93
8/8	63.12	.02	94
8/9	62.56	.05	95
8/10	64.44	0	94
8/11	57.57	.01	92
8/12	63.54	0	97
8/13	56.07	.11	92
8/14	59.26	0	88
8/15	61.09	0	93
8/16	59.28	0	92
8/17	63.63	0	94
8/18	58.16	0	97
8/19	59.92	0	100
8/20	64.45	0	96
8/21	65.06	0	95
8/22	61.46	0	93
8/23	60.96	0	95
8/24	63.64	0	95
8/25	59.27	0	94
8/26	57.14	0	95
8/27	61.72	0	97
8/28	60.79	0	94
8/29	60.99	0	95
8/30	58.38	0	95
8/31	60.89	0	91
9/1	58.6	0	91
9/2	54.41	.38	88
9/3	55.4	2.13	84
9/4	52.91	.27	86
9/5	55.3	0	86
9/6	54.9	0	87
9/7	53.06	0	91
9/8	53.92	0	91
9/9	51.72	0	92
9/10	81.78	0	91
9/11	58.47	0	90
9/12	56.65	0	91
9/13	55.25	0	88
9/14	58.48	0	89
9/15	57.58	0	91
9/16	53.05	0	82
9/17	55.34	0	83

9/18	53.61	.03	80
9/19	56.66	0	86
9/20	55.75	.18	82
9/21	51.26	0	80
9/22	53.32	0	90
9/23	54.71	0	91
9/24	56.15	0	91
9/25	57.48	0	89
9/26	57.92	0	86
9/27	58.04	0	85
9/28	54.88	0	82
9/29	53.48	.04	67
9/30	46.37	0	74
10/1	52.6	0	78
10/2	51.59	0	80
10/3	51.26	0	85
10/4	50.82	0	86
10/5	48.49	0	89
10/6	49.58	.05	89
10/7	51.67	2.43	89
10/8	47.93	.56	85
10/9	48.89	0	83
10/10	47.17	.64	85
10/11	53.37	0	86
10/12	49.77	0	85
10/13	51.63	.12	84
10/14	46.01	1.6	87
10/15	49.03	0	88
10/16	48	0	92
10/17	47.14	0	83
10/18	55.6	0	87
10/19	50.72	0	86
10/20	47.97	0	86
10/21	49.8	.84	87
10/22	46.8	0	70
10/23	48.91	.04	64
10/24	44.75	0	67
10/25	46.58	.04	83
10/26	46.76	.16	84
10/27	48	.01	85
10/28	48.03	0	87
10/29	47.36	0	84
10/30	48.49	0	86
10/31	52.37	0	86
11/1	52.67	0	87
11/2	54.65	1.17	76
11/3	52.55	0	71
11/4	48.24	0	79
11/5	50.97	0	75
11/6	50.73	0	80
11/7	51	0	81
11/8	51.03	0	83
11/9	51.57	0	84

11/10	51.53	0	77
11/11	49.56	0	70
11/12	52.23	0	75
11/13	53.11	0	77
11/14	50.67	0	80
11/15	53.52	0	83
11/16	54.72	.42	83
11/17	53.81	0	81
11/18	56.66	.1	76
11/19	53.25	0	63
11/20	51.48	0	51
11/21	51.69	0	60
11/22	49.36	0	58
11/23	52.79	0	63
11/24	52.45	0	74
11/25	52.98	0	79
11/26	53.75	0	82
11/27	52.54	.02	68
11/28	48.83	0	67
11/29	53.73	0	79
11/30	52.16	0	78
12/1	50.04	0	76
12/2	49.64	0	81
12/3	49.37	.05	62
12/4	45.34	.16	58
12/5	48.5	.04	53
12/6	48.76	0	56
12/7	48.88	0	59
12/8	51.35	0	74
12/9	51.9	0	80
12/10	54.37	0	80
12/11	54.39	0	80
12/12	52.95	0	80
12/13	54.95	0	82
12/14	54.7	0	78
12/15	54.22	0	78
12/16	51.4	.01	72
12/17	55.12	0	80
12/18	57.13	0	81
12/19	55.41	0	80
12/20	55.01	0	80
12/21	58.52	0	84
12/22	43.4	.15	70
12/23	55.82	.03	74
12/24	52.64	0	80
12/25	51.35	0	67
12/26	47.89	0	68
12/27	51.16	.01	81
12/28	52.51	0	80
12/29	54.51	0	81
12/30	46.08	0	79
12/31	52.53	.47	81

Corpus Christi, Texas - 1985

Date	Water Use (MGD)	Rainfall (INCHES)	Max. Temp. (F)
1/ 1	48.41	0	64
1/ 2	52.22	.35	43
1/ 3	60.37	.28	53
1/ 4	59.41	0	59
1/ 5	53.62	0	60
1/ 6	51.26	0	67
1/ 7	52.08	0	67
1/ 8	52.14	0	69
1/ 9	52.37	0	74
1/10	50.66	.02	67
1/11	52.03	.21	52
1/12	49.16	.69	37
1/13	63.24	.2	33
1/14	60.29	.04	46
1/15	54.41	0	54
1/16	54.68	.06	55
1/17	51.53	0	58
1/18	54.12	0	70
1/19	54.81	0	75
1/20	63.73	0	58
1/21	71.17	0	40
1/22	66.4	0	45
1/23	63.53	0	47
1/24	56.53	0	59
1/25	57.38	0	72
1/26	61.67	.16	60
1/27	59.17	.67	73
1/28	51.58	0	58
1/29	57.55	0	73
1/30	57.58	0	76
1/31	66.18	0	66
2/ 1	73.91	0	31
2/ 2	72.71	0	42
2/ 3	71.98	0	42
2/ 4	56.01	.14	46
2/ 5	67.42	0	48
2/ 6	64.14	0	45
2/ 7	55.16	0	55
2/ 8	61.66	0	58
2/ 9	54.05	0	72
2/10	51.47	0	74
2/11	54.77	0	60
2/12	57.11	0	64
2/13	56.36	0	70
2/14	53.65	.27	61
2/15	58.43	0	66
2/16	60.05	0	70
2/17	58.49	0	73
2/18	60.58	0	73

2/19	56.65	0	72
2/20	55.77	0	75
2/21	57.27	0	76
2/22	48.49	0	79
2/23	57.95	.04	74
2/24	44.18	1.1	64
2/25	46.71	0	67
2/26	57.34	.01	66
2/27	52.4	1.26	60
2/28	48.48	.04	61
3/ 1	55	0	67
3/ 2	54.85	0	76
3/ 3	55.69	0	78
3/ 4	56.12	0	73
3/ 5	55.64	0	61
3/ 6	52.47	0	66
3/ 7	60.92	0	78
3/ 8	56.11	0	81
3/ 9	59.2	0	78
3/10	57.83	0	81
3/11	62.54	0	83
3/12	60.86	0	81
3/13	58.88	0	80
3/14	49.64	.18	72
3/15	54.63	1.35	57
3/16	53.62	.07	60
3/17	52.47	0	65
3/18	53.5	0	66
3/19	55.66	0	72
3/20	57.46	.22	78
3/21	57.62	0	72
3/22	59.82	0	73
3/23	60.78	0	82
3/24	61.44	0	80
3/25	57.39	0	78
3/26	59.69	0	79
3/27	62.7	0	84
3/28	61.05	0	83
3/29	64.14	0	77
3/30	62.52	0	78
3/31	64.46	0	74
4/ 1	65.2	0	77
4/ 2	64.47	0	79
4/ 3	66.6	0	81
4/ 4	70.93	0	81
4/ 5	73.19	0	86
4/ 6	67.78	0	82
4/ 7	67.99	0	78
4/ 8	64.38	.17	70
4/ 9	57.59	.02	73
4/10	60.4	1.46	69
4/11	58.77	1.24	78
4/12	62.35	.13	78

4/13	63.1	.07	78
4/14	64.44	0	80
4/15	59.68	0	87
4/16	64.8	0	88
4/17	65.37	0	81
4/18	66.59	0	80
4/19	62.21	0	79
4/20	60.03	0	82
4/21	68.82	0	81
4/22	63.5	0	82
4/23	66.24	0	84
4/24	72.44	0	84
4/25	71.48	.38	80
4/26	65.01	0	81
4/27	64.81	0	80
4/28	63.41	.07	81
4/29	63.84	0	82
4/30	69.45	0	84
5/ 1	66.48	0	89
5/ 2	66.68	0	85
5/ 3	64.23	0	85
5/ 4	66.89	0	84
5/ 5	64.43	0	82
5/ 6	67.48	0	85
5/ 7	73.28	0	87
5/ 8	71.93	.36	90
5/ 9	69.35	0	89
5/10	67.16	0	87
5/11	70.1	0	87
5/12	71.35	0	87
5/13	71.16	0	87
5/14	68.46	0	84
5/15	69.5	0	86
5/16	70.37	0	86
5/17	65.82	.45	84
5/18	67.1	1.17	83
5/19	64.15	0	83
5/20	64.19	0	86
5/21	60.28	.7	80
5/22	61.99	0	87
5/23	65.04	0	86
5/24	64.51	.19	87
5/25	65.99	0	86
5/26	61.75	0	85
5/27	64.6	0	87
5/28	67.46	0	87
5/29	67.74	0	89
5/30	70.94	0	93
5/31	71.44	0	92
6/ 1	71.67	0	88
6/ 2	70.22	0	89
6/ 3	70.59	0	88
6/ 4	70.38	0	87

6/ 5	68.69	0	85
6/ 6	69.91	0	88
6/ 7	68.34	0	92
6/ 8	71.06	0	93
6/ 9	78.1	0	89
6/10	74.59	0	90
6/11	76.42	0	91
6/12	74.16	.01	91
6/13	72.04	1.59	86
6/14	65.52	0	87
6/15	70.27	0	88
6/16	76.57	0	89
6/17	72.91	0	91
6/18	69.36	.19	83
6/19	68.07	.73	82
6/20	65.74	1.29	83
6/21	59.8	.05	87
6/22	66.02	0	89
6/23	63.66	.13	89
6/24	63.43	0	88
6/25	70.99	0	88
6/26	72.08	0	89
6/27	63.97	0	91
6/28	73.73	0	82
6/29	62.83	0	87
6/30	69.77	0	87
7/ 1	70.94	0	89
7/ 2	70.22	.6	88
7/ 3	69.48	0	89
7/ 4	65.5	.43	87
7/ 5	64.99	0	88
7/ 6	65.89	0	90
7/ 7	70.22	0	87
7/ 8	64.33	.01	89
7/ 9	73.78	0	91
7/10	74.71	0	91
7/11	79.86	0	91
7/12	78.83	0	91
7/13	77.56	0	91
7/14	75.78	0	91
7/15	74.65	0	90
7/16	79.81	0	93
7/17	76.8	0	94
7/18	80.47	0	93
7/19	84.57	0	89
7/20	83.33	0	92
7/21	80.61	0	92
7/22	85.5	0	92
7/23	84.28	0	92
7/24	87.27	0	93
7/25	88.87	0	93
7/26	90.52	0	94
7/27	94.46	0	94

7/28	95.09	0	96
7/29	85.11	0	95
7/30	89.88	0	94
7/31	89.38	0	95
8/ 1	91.69	0	95
8/ 2	92.16	0	97
8/ 3	95.28	0	95
8/ 4	89.47	0	95
8/ 5	96.82	0	95
8/ 6	90.04	0	95
8/ 7	94.26	0	95
8/ 8	92.73	0	94
8/ 9	96.7	0	94
8/10	93.17	0	94
8/11	90.19	0	95
8/12	89.92	.63	92
8/13	93.27	0	93
8/14	84.38	0	92
8/15	96.48	0	96
8/16	92.55	0	96
8/17	95.79	0	94
8/18	94.89	0	98
8/19	92.16	0	97
8/20	98.09	0	95
8/21	99.61	0	95
8/22	95.48	0	94
8/23	92.9	0	95
8/24	95.16	0	96
8/25	87.86	0	96
8/26	96.64	0	97
8/27	93.43	0	94
8/28	83.71	1.11	86
8/29	68.04	1.14	86
8/30	71.29	0	90
8/31	69.69	0	93
9/ 1	69.07	0	95
9/ 2	72.77	0	98
9/ 3	79.96	0	95
9/ 4	80.02	0	92
9/ 5	76.44	0	92
9/ 6	80.5	0	93
9/ 7	75.58	0	93
9/ 8	83.04	0	93
9/ 9	83.58	0	92
9/10	74.67	0	90
9/11	69.49	.08	85
9/12	66.43	.2	89
9/13	68.37	0	89
9/14	70.61	0	91
9/15	66.56	.01	85
9/16	63.69	.89	86
9/17	63.47	.72	89
9/18	63.1	0	90

9/19	70.53	0	89
9/20	65.73	0	87
9/21	67.19	.41	81
9/22	64.08	0	88
9/23	64.37	0	92
9/24	70.17	0	87
9/25	63.29	0	91
9/26	65.08	.02	81
9/27	62.26	0	85
9/28	61.91	.16	86
9/29	58.03	5.3	90
9/30	59.53	.6	69
10/ 1	61.36	0	73
10/ 2	60.17	0	78
10/ 3	59.17	0	83
10/ 4	65.81	0	90
10/ 5	61.59	0	77
10/ 6	62.83	0	80
10/ 7	62.68	0	85
10/ 8	68.1	0	87
10/ 9	64.21	0	87
10/10	65.54	0	90
10/11	68.18	0	88
10/12	63.17	0	89
10/13	67.63	.07	89
10/14	65.11	0	90
10/15	65.04	1.05	82
10/16	60.48	0	80
10/17	63.02	.49	88
10/18	60.71	0	88
10/19	65.5	.04	89
10/20	61.18	.01	84
10/21	61.78	1.62	81
10/22	63.92	.12	82
10/23	67.99	0	87
10/24	65.15	0	87
10/25	63.23	0	85
10/26	62.69	0	84
10/27	63.32	0	82
10/28	63.9	0	83
10/29	63.58	0	80
10/30	62.65	0	74
10/31	73.79	0	77
11/ 1	61.5	.42	82
11/ 2	61.92	.38	62
11/ 3	59.13	0	71
11/ 4	65.51	0	74
11/ 5	62.93	0	75
11/ 6	60.57	0	82
11/ 7	70.23	0	73
11/ 8	65.85	0	83
11/ 9	62.44	0	82
11/10	64.28	0	81

11/11	66.22	.03	83
11/12	64.78	0	83
11/13	69.64	0	83
11/14	66.01	.16	82
11/15	66.31	0	85
11/16	60.3	0	64
11/17	58.12	0	82
11/18	65.79	0	82
11/19	63.99	0	83
11/20	60.87	0	67
11/21	61.69	0	67
11/22	60.78	0	74
11/23	59.03	.02	78
11/24	64.48	0	83
11/25	68.99	0	83
11/26	65.39	0	82
11/27	59.65	.61	74
11/28	54.57	0	64
11/29	53.61	0	66
11/30	59.25	0	80
12/ 1	56.15	0	73
12/ 2	54.6	0	51
12/ 3	61.05	0	55
12/ 4	58.79	0	70
12/ 5	58.06	0	66
12/ 6	59.97	0	66
12/ 7	55.17	0	77
12/ 8	57.12	0	77
12/ 9	60.63	0	79
12/10	60.14	.1	78
12/11	55.18	.92	73
12/12	55.78	.1	43
12/13	54.59	0	50
12/14	66.79	0	47
12/15	53.33	0	60
12/16	61.62	0	67
12/17	54.24	.42	54
12/18	56.83	.07	63
12/19	55	0	60
12/20	60.85	0	64
12/21	56.64	0	66
12/22	56.72	0	72
12/23	60.37	0	70
12/24	61.24	0	66
12/25	50.09	0	53
12/26	57.21	0	63
12/27	59.61	0	74
12/28	59.93	0	61
12/29	53.93	0	65
12/30	62.67	0	80
12/31	62.83	0	73