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Short-Term Water Dynamics in Chihuahua City, Mexico

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Abstract

Time series analysis of water consumption patterns has not been investigated on a wide scale basis. For many municipalities, such efforts offer a means for developing potentially useful planning tools. Because data requirements are not extensive, model development is feasible in most areas of the world. The work at hand examines the applicability of such a tool in Chihuahua City, an important metropolitan economy in Northern Mexico. Sample data are from January 1988 through December 2000. In addition to estimating a linear transfer function equation of water consumption in this city, the model is subjected to a series of simulation benchmark tests.

Keywords: water consumption, transfer function ARIMA analysis, forecast evaluation.

Index Terms: 6314 Policy Sciences: Demand estimation; 6334 Policy Sciences: Regional planning; 6399 Policy Sciences: General.

Introduction

Time series analysis of the stationary components of geographic water consumption patterns has not been carried out very extensively (Billings and Jones, 1996). For many municipalities, such efforts offer a means for developing potentially useful planning tools. Because data requirements are not extensive, model development is feasible for most areas of the world, including developing countries. The work at hand examines the applicability of such a tool in Chihuahua City, a rapidly growing metropolitan economy in Northern Mexico that, on average, receives less than 17 inches of rainfall per year (Durán, 1995). Sample data are from January 1988 through December 2000. In addition to estimating a linear transfer function equation of water consumption in this city, the model is subjected to a series of simulation benchmark tests.

Development of a planning model such as this is of interest in Chihuahua City from another perspective. Model maintenance and parameter re-estimation is straightforward and relatively easy to accomplish. Given that, a system of this nature is more likely to survive the 4-year managerial and administrative staff turnovers associated with the gubernatorial electoral cycle in the State of Chihuahua. Historically, planning analytics at the Junta Municipal del Agua y Saneamiento (JMAS) in Chihuahua City have been complicated by the political process. Models with manageable maintenance requirements are intuitively appealing under these circumstances.

The methodology employed belongs to the general area of transfer function autoregressive-moving average (ARIMA) time series models (Box and Jenkins, 1976). This approach is selected because it allows incorporating the influence of independent variables within a framework that also includes univariate time series components of the dependent variable. To carry out the analysis, a linear transfer function (LTF) procedure is employed (Liu and Hanssens, 1982). The latter has been shown to be useful in regional econometric research due to its emphasis on the roles played by right-hand-side regressors in time series modeling (Trívez and Mur, 1999). In addition to the standard diagnostics, model reliability is also assessed via a series of out-of-sample simulation exercises (Leamer, 1983; McCloskey and Ziliak, 1996).

Literature Review

Regional and metropolitan water consumption modeling has been a subject of ongoing interest in recent decades. Most of these efforts focus on residential water consumption and obtain fairly good empirical results (Gottlieb, 1963; Howe and Linaweaver, 1967; Gibbs, 1978; Danielson, 1979; Griffin and Chang, 1990; Pint, 1999). A smaller number of studies have examined commercial, industrial, and other nonresidential usage patterns (DeeRooy, 1974; Rensetti, 1988; Fullerton and Schauer, 2001). Similar exercises have also been completed for rural areas (Grunwald, Haan, Debertin, and Carey, 1976; Michelsen, Taylor, and Taylor, 1998). While a large number of papers indicate that public education, rationing, and other regulatory efforts improve efficiency, an even higher percentage highlight the importance of effective pricing and pricing structures (Camp, 1978; Agthe and Billings, 1980; Carver and Boland, 1980; Chicoine and Ramamurthy, 1986; Nieswiadomy and Molina, 1991; Nieswiadomy, 1992; Nauges and Thomas, 2000).

A range of price elasticities has been reported in the studies to date on water consumption. For residential clients, estimates typically fall between –0.15 and –0.8 (Billings and Jones, 1996; Pint, 1999; Brookshire, Burness, Chermak, and Krause, 2002). Two studies reports little difference between single-family residential and multi-family residential price responsiveness (Fullerton and Schauer, 2001; Agthe and Billings, 2002).

Commercial customer price elasticities generally fall within a very similar range to that of residential customers (Griffin and Chang, 1990; Billings and Jones, 1996). The latter is probably due to fairly similar usage patterns between the two rate categories: bathrooms and kitchens for indoor purposes, landscaping for outdoor purposes. Price elasticities of demand for industrial accounts tend to vary substantially (Billings and Jones, 1996). That dispersion is not surprising. There is no common usage pattern that characterizes the many types of manufacturing processes encountered in different regional economies.

A principal constraint encountered by multiple studies of water demand is the absence of good price documentation, irrespective of the geographic market being analyzed (Nauges and Thomas, 2000). Consequently, a large number of the papers published are precluded from utilizing marginal prices in the empirical analyses undertaken. For many areas, the only feasible approach to obtaining a price measure is to divide water and sewage revenues by total gallons (or cubic meters) consumed (Fullerton and Schauer, 2001). While such a strategy provides only a rough approximation of average prices, arguments presented by Nieswiadomy and Molina (1991) indicate that these types of estimates may provide accurate gauges of the basic information monitored by household and small business utility customers. Fortunately, statistical diagnostics obtained using these measures frequently exhibit good econometric traits.

While municipal utility price data are often difficult to obtain, monthly consumption data by rate class are generally available in many metropolitan markets. Despite the availability of this information, autoregressive-moving average (ARIMA) analyses of urban water consumption time series have not been very common (Billings and Jones, 1996). Given their usefulness in short-term planning exercises, it is surprising that univariate and multivariate ARIMA modeling techniques have not been more widely applied in this setting. Time series studies of other public utility consumption patterns have been successfully completed using ARIMA methodologies. Examples include natural gas (Liu and Lin, 1991) and electricity (Tserkezos, 1992; Fullerton, 1998).

Material below reviews results associated with an effort to model monthly water consumption in Chihuahua City, Mexico. In that respect, it is similar to the analysis conducted for Salt Lake City by Hansen and Narayanan (1981). The material below, however, does so within an ARIMA time series context that is similar to what has been utilized in several recent stream flow studies (Lungu and Sefe, 1991; Bender and Siminovic, 1994; Papamichail and Georgiou, 2001). As indicated by those efforts, ARIMA modeling approaches to water dynamics offer potentially helpful solutions with minimal data requirements.

Data and Methodology

Chihuahua City is the capital and second largest city in the State of Chihuahua in Northern Mexico. Home to more than 680 thousand persons, its demographic base is expanding fairly rapidly. Employment is also growing quickly, especially in the broadly defined manufacturing and commercial sectors of the metropolitan economy (Fullerton and Tinajero, 2002). Given these conditions, it is not surprising that the demand for new water system hook-ups has been very strong in recent years. Because water supplies are limited in the northern semi-arid region of Mexico, urban planning efforts in Chihuahua City are increasingly important.

Municipal water system consumption and revenue data records are available at a monthly frequency from January 1988 to December 2000 in Chihuahua City (JMAS, Junta Municipal de Agua y Saneamiento de Chihuahua, 2001). The data include meters in operation, cubic meters sold, and total revenues (water and sewer) in pesos. These time series allow a per customer, or per meter, consumption series to be estimated across all rate classes, as well as an effective price measure for total water consumed. The average rate variable is deflated to real terms using the monthly consumer price index series maintained by the central bank research department (Banco de México, www.banxico.org.mx). In addition to the real price variable, a monthly index of industrial activity is also utilized as an indicator of overall economic conditions in the empirical analysis (INEGI, Instituto Nacional de Estadística, Geografía, e Informática, www.inegi.gob.mx). Earlier demand studies present ample documentation of the importance of rainfall and other climatic data for municipal water consumption (Hansen and Narayanan, 1981; Fullerton and Schauer, 2001). Monthly total rainfall and average ambient temperature data for Chihuahua City are employed in the analysis detailed below (CONAUGUA, Consejo Nacional del Agua, 2002). Summary statistics for each of the time series utilized are reported in Table 1. The data are available upon request from the authors.

Table 1
Summary Statistics

Variable	Mean	Standard Deviation
Water per Meter	59.206	26.515
Real Price	45.674	6.069
Industrial Production	105.186	16.145
Rainfall	34.122	53.068
Temperature	19.068	6.069

Sample Period: January 1980 – December 2000
Chihuahua City Monthly Water Consumption per Customer in Cubic Meters
Chihuahua City Average Real Price, 1995 Pesos per Cubic Meter
Mexico Industrial Production Index, 1993 = 100
Monthly Rainfall in Millimeters
Average Monthly Temperature, Centigrade

Stationary components of the data, defined as first and second moments that do not change over time, are modeled using an LTF ARIMA procedure. Cross correlation function (CCF) estimates are estimated as a means for identifying the lag structures that potentially characterize the relationships between per customer consumption and the independent variables. To investigate the potential dynamic relationship between the stationary component of the per customer water consumption dependent variable *w* and an arbitrary stationary independent variable *x* with lag *k*, cross correlation functions (CCFs) of the form shown in Equation 1 are estimated (Wei, 1990). In Equation 1, deviations relative to variable means appear in the numerator, while standard deviations are used in the denominator.

$$\hat{r}_{xw}(k) = \frac{\sum_{t=1}^{T-k}(x_t - \bar{x})(w_{t+k} - \bar{w})}{\hat{\sigma}_x \hat{\sigma}_w}, \text{ for k = 0,1,2,…, and t = 1,2,…,T.} \qquad (1)$$

Once an initial transfer lag structure between the dependent and independent variables is identified, a transfer ARIMA equation is estimated. Following parameter estimation, standard diagnostic checking is carried out to examine what input variable lags should be retained. Under the LTF approach, any remaining systematic movements in the dependent variable are then modeled using a combination of autoregressive and moving average parameters (Liu and Hanssens, 1982; Trívez and Mur, 1999). Several rounds of diagnostic checking and re-estimation are generally required before a final transfer model specification is selected (Box and Jenkins, 1976; Wei, 1990). The general function format for modeling short-term per customer water consumption trends can be summarized as:

$$w_t = \theta_0 + \sum_{i=1}^{p} \phi_i w_{t-i} + \sum_{j=1}^{q} \theta_j e_{t-j} + \sum_{a=1}^{A} a_a RP_{t-a} + \sum_{b=1}^{B} b_b IND_{t-b} + \sum_{c=1}^{C} c_c RAIN_{t-c} + \sum_{d=1}^{D} d_d TEMP_{t-d} + e_t, \qquad (2)$$

$$\underset{}{NLMQ_t} = f(\underset{(-)}{\text{Real Wages}_{t-i}}, \underset{(+)}{\text{Real Peso}_{t-j}}, \underset{(+)}{\text{Factories}_{t-k}}, \underset{(+)}{\text{U.S. Ind. Act.}_{t-m}}, AR_{t-n}, MA_{t-s})$$

where:

w_t = Chihuahua City water consumption, cubic meters per customer in month t,
RP_t = Chihuahua City average monthly real price variable measured in 1995 pesos,
IND_t = Mexico industrial activity, 1993 = 100,
$RAIN_t$ = Chihuahua City total monthly precipitation measured in millimeters, and
$TEMP_t$ = Chihuahua City average monthly ambient temperature, degrees Celsius.

The sum of the coefficients for lags of the real price variable in Equation 2 is hypothesized to be negative. For the industrial production index, the sum of the regression parameters is expected to be positive because increases (decrease) in economic activity will cause municipal water consumption to increase (decrease). Greater rainfall is expected to reduce consumption, so the sum of the parameters for that variable is hypothesized as less than zero. Higher temperatures affect water usage in a direct manner and the sum of the regression coefficients for that variable is expected to be positive. Algebraic signs for the autoregressive and moving average parameters are ambiguous. Time lags are allowed to vary for each of the explanatory variables as well as for the autoregressive and moving average parameters used to eliminate serial correlation.

Good in-sample fits frequently fail to guarantee out-of-sample simulation accuracy (Leamer, 1983; McCloskey and Ziliak, 1996). Accordingly, a set of benchmark simulations is also employed as a means for testing model reliability (Granger, 1996; Fullerton, Luevano, and West, 2000). Simulation outcomes for the different methodologies are then assessed using a combination of Theil U-statistics and modified Theil inequality coefficients (Webb, 1984; Pindyck and Rubinfeld, 1998).

Following parameter estimation, a 36-month out-of-sample simulation exercise is conducted. First, a sub-sample estimation period is defined from January 1988 to December 1997 with a forecast period from January 1998 to December 1998. Next, the estimation period is expanded by one month to January 1998 and the forecast period is rolled forward to February 1998 through January 1999. A total of 36 estimation and simulation exercises are conducted through December 2000. This results in 36 one-month employment forecasts, 35 two-month forecasts, 34 three-month forecasts, and so forth.

In addition, an easier to construct random walk set of forecasts is compiled using only the latest available historical observation as the prediction for all periods falling beyond the sample range. Random walk benchmarks constructed in this manner frequently out-perform time series and econometric equation counterparts in simulation comparisons conducted for regional markets (Fullerton, Luevano, and West, 2000). The out-of-sample simulations generated by the LTF model and the random walk techniques are each segregated into step-length forecasts. The segregated data for both methodologies are then compared to actual Chihuahua City per meter water consumption levels.

Prediction errors are used to calculate root mean square error (RMSE) values for all 12-month step-lengths as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(w_t^s - w_t^a)^2} \qquad (3)$$

where w_t^s is the forecast value for w_t,, w_t^a is the actual value, and T is the number of simulation observations for each step-length.

Theil inequality coefficients are also computed for each set of forecasts (Pindyck and Rubinfeld, 1998). They are calculated as shown in Equation 4:

$$U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(w_t^s - w_t^a)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(w_t^s)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(w_t^a)^2}} \quad . \tag{4}$$

The Theil inequality coefficients are also decomposed in the following manner:

$$U^M = \frac{(\overline{w}^s - \overline{w}^a)^2}{(1/T)\sum(w_t^s - w_t^a)^2} \ ,$$

$$U^S = \frac{(\hat{\sigma}_s - \hat{\sigma}_a)^2}{(1/T)\sum(w_t^s - w_t^a)^2} \ ,$$

and

$$U^C = \frac{2(1-\hat{\rho})\hat{\sigma}_s\hat{\sigma}_a}{(1/T)\sum(w_t^s - w_t^a)^2} \quad . \tag{5}$$

The decomposition of the inequality statistic is designed to measure forecast bias (U^M), variance (U^S), and covariance (U^C) proportions. The bias proportion is an indication of systematic error; the variance proportion indicates the ability of the model to replicate the degree of variability in the variable of interest; and the covariance proportion measures unsystematic error. Consequently, for any value U>0, the ideal distribution of inequality over the three sources is $U^M = U^S = 0$ and $U^C = 1$ (Pindyck and Rubinfeld, 1998).

Modified Theil inequality coefficients are also tabulated for each of the forecast step-lengths. This last set of comparison data utilizes the ratios of the LTF RMSEs to those of the benchmark forecasts to compare out-of-sample simulation accuracy (Webb, 1984). A modified Theil inequality coefficient less than 1.0 implies that the LTF simulations are more accurate than their random walk counterparts for that particular number of months ahead being forecast. Conversely, when a modified Theil inequality coefficient exceeds 1.0, it implies that the LTF simulations are less accurate than the random walk extrapolations for that specific step-length. Although forecast error serial correlation prevents using RMSE-based measures in formal hypothesis tests, these descriptive measures have been shown to provide reliable rankings of prediction accuracy (Mizrach, 1992; West, 1996).

Empirical Results

Estimation results for the LTF equation appear in Table 2. The lag structure exhibited by the model is fairly short. Price variables are included with lags of 1 and 5 months. Industrial production coefficients are estimated at lags of 4 and 13 months. One-month lags of the temperature and rainfall variables are also included in the model. The constant term is negative and statistically significant. Given that the data are differenced prior to estimation, that result reflects a downward trend in water consumption per meter over the sample period in question and indicates that the Chihuahua City water utility (JMAS) conservation programs are at least partially successful.

Table 2
Chihuahua City Per Customer Water Consumption LTF ARIMA Model

Variable	Coefficient	Standard Error	t-Stat.	Prob.
Constant	-0.680	0.290	-2.341	0.0207
Real Price (-1)	-2.404	3.500	-0.687	0.4933
Real Price (-5)	-3.510	3.445	-1.019	0.3100
Industrial Production (-4)	0.117	0.052	2.244	0.0264
Industrial Production (-13)	0.098	0.054	1.813	0.0721
Average Temperature (-1)	0.255	0.056	4.560	0.0001
Average Rainfall (-1)	-0.004	0.004	-1.077	0.2835
MA (8)	0.225	0.088	2.566	0.0114

R-squared	0.204	Dependent variable mean	-0.601
Adjusted R-squared	0.162	Dependent variable std. dvn.	3.093
S.E. of regression	2.831	Akaike criterion	4.974
Sum of squared residuals	1073.983	Schwarz criterion	5.140
Pseudo R-squared	0.976	Q-Statistic (18)	1.0225
Log likelihood	-345.144	F-statistic	4.903
Durbin-Watson statistic	1.804	F-statistic probability	0.0001

Sample Period: January 1988 – December 2000
Iterations to Convergence: 10

While all of the Table 2 coefficient signs for the independent variables are as hypothesized, several fail to satisfy the 5-percent significance criterion. Because the F-statistic for the overall specification is significant at the 1-percent level, the low t-values for individual regressors potentially reflect multicollinearity. The low t-statistics may also be due to attempting to model aggregate usage per customer without regard to JMAS customer categories. Unfortunately, at present, it is not feasible to disaggregate among residential, commercial, industrial, and other rate classes in Chihuahua City. That problem is not unique to this municipality and has also been encountered in data sets from other regions in Mexico (Fullerton and Schauer, 2001).

Because first-differences are used in the nonlinear regression analysis, both the coefficient of determination and the adjusted R-squared measures are fairly low. Transformation of the fitted data for the dependent variable to level form permits estimation of a Pseudo R-squared coefficient. That number indicates that the LTF equation explains approximately 98 percent of the variation in the dependent variable over the sample period in question. The Q-statistic is correspondingly very low and indicates that the equation does not fail to account for any systematic variation in the dependent variable for the sample estimation period.

As mentioned above, strong in-sample correlations do not always guarantee model simulation accuracy. To further examine model reliability, a series of rolling parameter re-estimation and out-of-sample simulations are conducted. That effort generates 36 1-month water consumption forecasts, 35 2-month forecasts, and so forth until 24 observations are simulated for the 12-month forecast period. Those forecasts are then compared to a random walk benchmark. Table 3 summarizes the out-of-sample LTF simulation results and Table 4 contains the random walk outcomes.

Table 3
Chihuahua City LTF Water Simulation Accuracy Results

	RMSE	**Theil-U**	**U^m**	**U^s**	**U^c**
One-Month Ahead	1.613	0.0194	0.0066	0.0058	0.9876
Two-Months Ahead	2.216	0.0267	0.0168	0.0216	0.9616
Three-Months Ahead	2.599	0.0313	0.0239	0.1041	0.8720
Four-Months Ahead	3.035	0.0366	0.0250	0.1360	0.8390
Five-Months Ahead	3.434	0.0415	0.0259	0.2162	0.7579
Six-Months Ahead	3.892	0.0472	0.0218	0.2799	0.6983
Seven-Months Ahead	4.435	0.0540	0.0247	0.2572	0.7181
Eight-Months Ahead	4.952	0.0608	0.0343	0.2242	0.7415
Nine-Months Ahead	5.471	0.0676	0.0400	0.2048	0.7552
Ten-Months Ahead	5.945	0.0741	0.0523	0.1679	0.7798
Eleven-Months Ahead	6.415	0.0806	0.0727	0.1606	0.7667
Twelve-Months Ahead	6.713	0.0851	0.0798	0.1888	0.7314

As generally occurs with multi-period forecasts, the LTF RMSEs rise as the number of months being simulated increases. The Theil inequality statistics for the LTF model exhibit good characteristics for all 12 time periods. The bias and variance proportions of the U-statistics are low for each set of extrapolation step-lengths. Consequently, the covariance proportions listed in the final column of Table 3 remain close to, or greater than, 70 percent mark for all periods considered and the transfer function equation out-of-sample forecasts provide apparently good approximations of the systematic movements in per meter water consumption in Chihuahua City.

The RW extrapolation results in Table 4 share several traits with those of the LTF model. The RMSE estimates in the first column of Table 4 rise in a monotonic fashion as a function of forecast step-length. The bias and variance components of the Theil inequality coefficients are also relatively low, although not as low as those obtained for the LTF equation. The covariance proportions of the U-statistics do not, however, fall below 42 percent for any of the forecast period groupings.

Table 4
Chihuahua City Random Walk Water Extrapolation Accuracy Results

	RMSE	Theil-U	U^m	U^s	U^c
One-Month Ahead	1.627	0.0195	0.0048	0.0528	0.9424
Two-Months Ahead	2.554	0.0305	0.0590	0.0809	0.8601
Three-Months Ahead	3.280	0.0390	0.0704	0.1097	0.8199
Four-Months Ahead	3.858	0.0487	0.0855	0.1281	0.7864
Five-Months Ahead	4.375	0.0527	0.1034	0.1548	0.7418
Six-Months Ahead	4.872	0.0585	0.1283	0.1716	0.7001
Seven-Months Ahead	5.307	0.0646	0.1515	0.1743	0.6742
Eight-Months Ahead	5.637	0.0695	0.1893	0.1690	0.6417
Nine-Months Ahead	5.997	0.0747	0.2266	0.1711	0.6023
Ten-Months Ahead	6.341	0.0777	0.2633	0.1833	0.5534
Eleven-Months Ahead	6.739	0.0824	0.3805	0.1908	0.4287
Twelve-Months Ahead	7.194	0.0888	0.3317	0.1919	0.4764

Table 5 provides a direct comparison of the relative accuracies of the two simulation methods. At all 12 step-lengths, the modified inequality ratios fall below the 1.0 threshold. Those data imply that the LTF approach provides a fairly reliable approach to short-term forecasting analysis for per customer water consumption in Chihuahua City. The modified Theil coefficients do not exhibit any distinct temporal patterns as the length of the simulation period increases. Although additional testing for future time periods in this market is recommended, especially in light of some of the weak diagnostics reported in Table 2, the LTF technique performs acceptably in the context of the out-of-sample forecasts performed for the January 1998 – December 2000 period analyzed.

Table 5
Chihuahua City LTF vs. RW Water Consumption Modified Theil U-Statistics

	LTF RMSE	RW RMSE	Modified Theil-U
One-Month Ahead	1.613	1.627	0.9914
Two-Months Ahead	2.216	2.554	0.8677
Three-Months Ahead	2.599	3.280	0.7924
Four-Months Ahead	3.035	3.858	0.7867
Five-Months Ahead	3.434	4.375	0.7848
Six-Months Ahead	3.892	4.872	0.7989
Seven-Months Ahead	4.435	5.307	0.8357
Eight-Months Ahead	4.952	5.637	0.8785
Nine-Months Ahead	5.471	5.997	0.9123
Ten-Months Ahead	5.945	6.341	0.9375
Eleven-Months Ahead	6.415	6.739	0.9519
Twelve-Months Ahead	6.713	7.194	0.9331

Conclusion

Time series analysis of the stationary components of per meter water consumption in Chihuahua City, Mexico is conducted for the January 1988 – December 2000 sample period. Chihuahua City is an important metropolitan economy in a semi-arid region of Northern Mexico. Income growth and demographic expansion are combining to accelerate the demand for additional municipal water system hook-ups in the city. An ARIMA linear transfer function methodology is utilized to model per customer water usage. The estimation results are augmented by out-of-sample simulation analyses.

Empirical estimation results are mixed, but fairly good. Although coefficient signs are as hypothesized, some of the computed t-statistics for the regressors fail to satisfy the 5-percent significance criterion. The equation F-statistic and the Pseudo R-squared measures are more encouraging. Out-of-sample simulation tests also exhibit good performance traits and compare favorably to a random walk benchmark.

Additional testing for other geographic markets would be helpful. Because data bank and model maintenance requirements are not severe, model development can be undertaken in developing as well as industrially advanced economies. When feasible, consumption by rate class should also be included in the analyses. Availability of such information is not universal, but it can be acquired for some regions. Rates data themselves are also frequently difficult to obtain, but can be at least partially overcome by employing revenue per gallon or revenue per cubic meter estimates. When the latter improvements are infeasible, however, the aggregate per customer approach adopted herein due to data constraints may provide a workable strategy.

References

Agthe, D.E., and R.B. Billings, 1980, "Dynamic Models of Residential Water Demand," *Water Resources Research* 16, 476-480.

Agthe, D.E., and R.B. Billings, 2002, "Water Price Influence on Apartment Complex Water Use," *Journal of Water Resource Planning and Management* 128, 366-369.

Banco de México, www.banxico.org.mx, web site.

Bender, M., and S. Siminovic, 1994, "Time Series Modeling for Long-Range Stream-Flow Forecasting," *Journal of Water Resource Planning and Management* 120, 857-870.

Billings, B., and C.V. Jones, 1996, *Forecasting Urban Water Demand*, Denver, CO: American Water Works Association.

Box, G.E.P., and G. Jenkins, 1976, *Time Series Analysis, Control, and Forecasting*, Second Edition, San Francisco, CA: Holden Day.

Brookshire, D.S., H.S. Burness, J.M. Chermak, and K. Krause, 2002, "Western Urban Water Demand," *Natural Resources Journal* 42, 871-898.

Camp, R.C., 1978, "The Inelastic Demand for Residential Water," *Journal of the American Water Works Association* 70, 453-458.

Carver, P. and J.J. Boland, 1980, "Short- and Long-Run Effects of Price on Municipal Water Use," *Water Resources Research* 16, 609-616.

Chicoine, D.L. and G. Ramamurthy, 1986, "Evidence on the Specification of Price in the Study of Domestic Water Demand," *Land Economics* 62, 26-31.

CONAGUA, Consejo Nacional del Agua, 2002, *Cuadros Meteorológicos Estatales*, Chihuahua City, MX: CONAGUA Gerencia Estatal.

Danielson, L.E., 1979, "An Analysis of Residential Demand for Water using Micro Time-Series Data," *Water Resources Research* 15, 763-767.

DeRooy, J., 1974, "Price Responsiveness of the Industrial Demand for Water," *Water Resources Research* 10, 403-406.

Durán, J.B., 1995, *Chihuahua: El Vital Líquido a través de los Tiempos*, Chihuahua, MX: Colección Textos Universitarios UACH.

Fullerton, T.M., Jr., 1998, "Cross Border Business Cycle Impacts on Commercial Electricity Demand," *Frontera Norte* 10, 53-66.

Fullerton, T.M., Jr., J.A. Luevano, and C.T. West, 2000, "Accuracy of Regional Single-Family Housing Start Forecasts," *Journal of Housing Research* 11, 109-120.

Fullerton, T.M., Jr., and D. Schauer, 2001, "Regional Econometric Assessment of Aggregate Water Consumption Trends," *Australasian Journal of Regional Studies* 7, 167-187.

Fullerton, T.M., Jr., and R. Tinajero, 2002, "Borderplex Economic Outlook: 2002-2004," *Business Report SR02-2*, El Paso, TX: UTEP Border Region Modeling Project.

Gibbs, K., 1978, "Price Variable in Residential Water Demand Models," *Water Resources Research* 14, 15-18.

Gottlieb, M., 1963, "Urban Domestic Demand for Water: A Kansas Case Study," *Land Economics* 39, 204-210.

Griffin, R.C., and C. Chang, 1990, "Pretest Analysis of Water Demand in Thirty Communities," *Water Resources Research* 26, 2251-2255.

Grunewald, O.C., C.T. Hann, D.U. Debertin, and D.I. Carey, 1976, "Rural Residential Water Demand: An Econometric and Simulation Analysis," *Water Resources Bulletin* 12, 951-961.

Hansen, R.D., and R. Narayanan, 1981, "A Monthly Time Series Model of Municipal Water Demand," *Water Resources Bulletin* 17, 578-585.

Howe, C.W., and F.P. Linaweaver, Jr., 1967, "The Impact of Price on Residential Water Demand and its relation to System Design and Price Structure," *Water Resources Research* 3, 13-32.

INEGI, Instituto Nacional de Estadística, Geografía, e Informática, www.inegi.gob.mx, web site.

JMAS, Junta Municipal de Agua y Saneamiento de Chihuahua, 2001, *Cuadro Comparativo de Facturación contra Presupuesto*, Chihuahua City, MX: JMAS.

Liu, L.M., and D.M. Hanssens, 1982, "Identification of Multiple-Input Transfer Function Models," *Communications in Statistics* 11, 297-314.

Liu, L.M., and M.W. Lin, 1991, “Forecasting Residential Consumption of Natural Gas using Monthly and Quarterly Time Series,” *International Journal of Forecasting* 7, 3-16.

Leamer, E.E., 1983, “Let’s take the Con out of Econometrics,” *American Economic Review* 73, 31-43.

Lungu, E.M., and F.T.K. Sefe, 1991, “Stochastic Analysis of Monthly Streamflows,” *Journal of Hydrology* 126, 171-182.

McCloskey, D.N., and S.T. Ziliak, 1996, “The Standard Error of Regressions,” *Journal of Economic Literature* 34, 97-114.

Michelsen, A.M., D.T. Taylor, R.G. Taylor, 1998, “Assessing Regional Indirect Water Use by Agricultural Industries,” *Cross Currents in Water Policy Proceedings*, Hood River, OR: Universities Council on Water Resources.

Mizrach, B., 1992, “The Distribution of the Theil U-statistic in Bivariate Normal Populations,” *Economics Letters* 38, 163-167.

Nauges, C. and A. Thomas, 2000, “Privately Operated Water Utilities, Municipal Price Negotiation, and Estimation of Residential Water Demand: The Case of France,” *Land Economics* 76, 68-85.

Nieswiadomy, M.L. and D. Molina, 1991, “A Note on Price Perception in Water Demand Models,” *Land Economics* 67, 352-359.

Nieswiadomy, M.L., 1992, “Estimating Urban Residential Water Demand: Effects of Price Structure, Conservation, and Education,” *Water Resources Research* 28, 609-615.

Papamichail, D.M., and P.E. Georgiou, 2001, “Seasonal ARIMA Inflow Models for Reservoir Sizing,” *Journal of the American Water Resources Association* 37, 877-885.

Pindyck, R.S., and D.L. Rubinfeld, 1998, *Econometric Models and Economic Forecasts*, Fourth Edition, New York, NY: Irwin McGraw-Hill.

Pint, E., 1999, “Household Responses to Increased Water Rates During the California Drought,” *Land Economics* 75, 246-266.

Rensetti, S., 1988, “An Econometric Study of Industrial Water Demands in British Columbia, Canada,” *Water Resources Research* 24, 1569-1573.

Trívez, F.J., and J. Mur, 1999, “A Short-Term Forecasting Model for Sectoral Regional Employment,” *Annals of Regional Science* 33, 69-91.

Tserkezos, E.D., 1992, “Forecasting Residential Electricity Consumption in Greece using Monthly and Quarterly Data,” *Energy Economics* 14, 226-232.

Webb, R.H., 1984, “Vector Autoregressions as a Tool for Forecast Evaluation,” Federal Reserve Bank of Richmond *Economic Review* 70, 3-11.

Wei, W.W., 1990, *Time Series Analysis: Univariate and Multivariate Methods*, New York, NY: Addison-Wesley.

West, C.T., 1996, “System-based Weights vs. Series-specific Weights in the Combination of Forecasts,” *Journal of Forecasting* 15, 369-383.