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# MODELING WATER INTAKE IN A CANADIAN HOUSEHOLD

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**ABSTRACT**

This article presents a model of water intake in a suburban Canadian household. The data cover daily water intake for a year. It is shown that a Box-Jenkins model with moving average terms best fits the data. Further, it is shown that a separate model for each of the three seasons provides an even better fit. The models are then explained with reference to water consumption habits and patterns.

## INTRODUCTION

Several models have been formulated to guide or explain water policy. Most are "macro" models in that they try to explain water use for countries, regions, or entire urban areas [1-6], or for industries [7-10], or for overall water policy management [11, 12]. Many important studies have assessed the impact of price on residential water demand [13-16]. Other studies have used climatic variables and price data [14, 17-20] to forecast water demand, taking advantage of significant advances in building time series models [21-26]. A distinguishing characteristic of these studies before the mid-1970's has been that most dealt with cross-sectional, not time series, data. The principal reason for this, as documented by Young [27] and Wong [28] is the limited availability of data. There has since been considerable progress in time series modeling [14, 18, 20-23, 29-31] as more time series data became available.

In most cases, however, the time series data are monthly figures for cities or regions only. "Micro" data for daily consumption at the household level are rare.





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Even then, daily data for household consumption over a year are hard to come by. Maidment et al. studied municipal water use [25]. Hughes reported on daily data for municipal systems [22]. Smith analyzed daily water use over a summer for the Washington, D.C., Metropolitan Area (WMA) [26]. Examples of specific modeling of single households in a micro context are very few. Most Canadian households consume large quantities of water in dish washing, washing clothes and lawn watering in addition to routine water use in cooking and in bathrooms. While dishwashing is normally a regular daily chore, clothes are collected and washed every two or three days, or weekly, depending on the size of the load. These two activities occur over the entire year. Lawn watering lasts from the end of May to late September or later, depending on the onset of wintry weather. Lawns are usually watered for a two-hour period. In a home with front and back lawns, a minimum four-hour watering each time is typical. During warm spells even six hours of watering may be needed. During these periods, there is a fall in water pressure and this may make intensive water use for other purposes such as dish or clothes washing difficult. Thus, the water use may be scheduled in such a way that each of these activities is carried out during different periods so that water use is likely evened out over the seven days of the week. An analysis of daily water intake over a period of a year could tell us much about these fluctuations in water use.

We present here a model for household water intake. Data were collected from a suburban house near Ottawa, Canada. A single family of two adults and three children formed the household. There are three bathrooms with three toilets, one tub and one shower in use. The family uses an automatic clothes washer and a dishwasher. The household is located in a subdivision provided with a community water supply and sewer system. The data consist of daily water intake figures over almost one full year. It may be preferable to model water consumption rather than water intake. But such consumption data are hard, if not impossible, to obtain. No municipality in Canada measures water use exclusive of water returned to source. The data reported here are not necessarily for the most recent period, but nevertheless are assumed to be representative since there is no reason to believe that average water intake would fluctuate widely, year to year in the absence of far reaching changes in climatic and/or economic conditions.

The daily data consist entirely of household water intake for one bungalow type house for each day of the week for forty-nine weeks beginning from the 1st of January. These figures are expressed in cubic meters per day. There were a few missing observations. These were replaced by the simple average of the average intake over the remaining days of the week and the annual average for that day over the other weeks in the forty-nine-week time horizon. Thus, we had a total of 343 data points to work with. These water intake figures are influenced by several factors such as number of people in the household, guests, special events which may increase or decrease people using water in the home over the entire day, temperature and humidity inside and outside, age distribution of the members of the household, and several other factors. Thus, the variation in water intake from day to day may be caused by several factors, the influence of each one of which may be too small or too difficult to measure; yet, their cumulative effects, while random, may yet be measurable. Instead of a regression or input-output model, a Box-Jenkins type "Auto Regressive Integrated Moving Average" (or ARIMA) model was chosen to fit the data.

In the next section, we briefly describe ARIMA models and the model selection procedure which then is applied in the following section. The annual data is broken down into three data periods to take seasonal variations into account. The last section discusses model results and policy implications.

## MODEL DESCRIPTIONS

The general ARIMA model with autoregressive terms of order 'p' and moving average terms of order 'q', is given by:

$$Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + a_t - \sum_{i=1}^{q} \theta_i a_{t-i}, \tag{1}$$

where $Y_t$ is the value of Y at time 't', $a_t$ is the random error term at time 't', assuming that the 'Y' values have a stationary mean. If not, they must be suitably differenced till stationarity in the mean is achieved. The $\phi_i$'s and the $\theta_i$'s are known as the autoregressive and moving average parameters of order 'i'. In addition, there may be seasonality in the data; for example, every Monday there may be a significant increase or decrease in water consumption indicating a seasonality of order 7 in the daily data. One distinguishing characteristic of the ARIMA models is parsimony, so that rarely do the autoregressive, moving average or differencing factors have values greater than 2. In economic and social science time series data, it rarely happens that both the autoregressive and moving average lags are non-zero [32]. The general notation for ARIMA models is ARIMA (p,d,q) $(P,D,Q)$s, where p,d,q represent the autoregressive, differencing and moving average lags required when no seasonality is observed, and P,D,Q represent their corresponding values when additional seasonal differencing is required to make the observations stationary.

The strategy for building ARIMA models for any given problem proceeds in well defined stages laid down by Box and Jenkins [33]. These are the four stages of Identification, Estimation, Diagnosis and Forecasting. First, the data and the scatter diagram were examined to check for stationarity. If the data do not look stationary they are differenced to the appropriate lag to ensure stationarity. Stationarity in this context means that the random process generating the data is in equilibrium around the underlying mean of the process and that the variance remains more or less constant over time. Then, one looks at the autocorrelation function (ACF) and the partial autocorrelation function (PACF) to search for patterns of autoregressive and/or moving average behaviour. There are well researched and documented procedures to arrive at initial estimates of these lags [32-34]. Any resulting ambiguity in model selection and interpretation may be resolved by looking at the various test statistics for the estimates derived from the empirical data. These procedures are now applied to model the water intake behaviour of a Canadian household, based on daily readings over forty-nine consecutive weeks.

## ARIMA MODEL OF THE DAILY WATER INTAKE DATA

The daily water intake data are shown in Table 1. Their empirical characteristics were analyzed first and the Box-Jenkins iterative model building strategy was followed to arrive at the appropriate ARIMA model. The ACF's (Auto Correlation Functions) and PACF's (Partial Auto Correlation Functions) of the raw data series are shown in Figures 1 and 2. They indicate nonstationarity. The series had to be differenced once to remove this nonstationarity. (The rest of this article therefore deals with this differenced series only.)

But even this differencing could only ensure stationarity in the mean at most. However, in the northern hemisphere, climatic fluctuations lead to wide variations in temperature and humidity—and in water use, as noted. It is reasonable to test for equality of means and equality of variances in water intake during the seasons: 1) winter (January-May), 2) spring and summer (June-September), and 3) fall (October-December). Since lawn watering starts in the spring, and continues till the end of summer, those two seasons were grouped together.

The mean daily water intake and the standard deviation of daily water intake are shown in Table 2, with the results of the statistical tests of equality of variances and of the means. Since the variances clearly are not equal, separate models were fitted for each seasonal group.

The winter data had 161 observations, the spring/summer data had 119, and the fall data 63. The ACF and PACF for these data sets are shown in Figures 3, 4, and 5, respectively. The winter ACF shows a significant spike at lag 1 and a less conspicuous one at lag 2 and then decays. Its PACF shows significant spikes at lags 1 and 2 and then gradually decays. This is more or less the same as the pattern for the annual data, and it suggests an ARIMA (0,1,2) model with positive moving average parameters at both lags. The parameters for both (0,1,1) and (0,1,2) models were estimated and the second lag parameter was found statistically significant. The residual ACF at all lags showed no significant autocorrelation at any lag. Accordingly, it was concluded that the residuals were 'white noise'. The parameter estimates obeyed the stationarity and invertibility conditions required. Only six of the 161 back forecasts were outside the forecast 95 percent confidence interval, the expected number being 8.

The ACF for the spring/summer period shows a single negative spike at lag 1 decaying thereafter; the same is true of the PACF. This suggests an ARIMA (0,1,1) model. Accordingly, the parameters were estimated for three models: ARIMA

Table 1. Water Consumption in Cubic Meters per Day

| Week | Day 1 | Day 2 | Day 3 | Day 4 | Day 5 | Day 6 | Day 7 |
|---|---|---|---|---|---|---|---|
| 1 | 1.10922 | 1.08195 | 1.13650 | 1.10922 | 1.25015 | 0.99557 | 1.13650 |
| 2 | 1.10922 | 1.19560 | 1.27743 | 1.27743 | 1.16378 | 1.08195 | 1.08195 |
| 3 | 1.22287 | 0.96830 | 1.05013 | 1.08195 | 1.16378 | 1.13650 | 0.96830 |
| 4 | 1.20924 | 1.20469 | 1.20924 | 1.27743 | 1.05013 | 1.45017 | 1.39108 |
| 5 | 1.19560 | 1.05013 | 0.82283 | 1.16378 | 0.82283 | 1.07286 | 1.07740 |
| 6 | 1.17741 | 1.16378 | 1.36380 | 1.42290 | 1.10922 | 1.19560 | 1.16378 |
| 7 | 1.19560 | 1.30925 | 1.13650 | 1.13650 | 1.84568 | 1.70475 | 1.33652 |
| 8 | 1.19560 | 1.30925 | 1.13659 | 1.17287 | 1.18196 | 1.17741 | 1.17740 |
| 9 | 1.22287 | 0.96830 | 0.82283 | 0.93648 | 1.08195 | 0.93648 | 0.93846 |
| 10 | 0.93648 | 0.88192 | 0.88912 | 0.68190 | 0.90920 | 0.05910 | 0.42732 |
| 11 | 0.93648 | 0.90920 | 1.02285 | 0.90920 | 0.90290 | 0.99557 | 0.99575 |
| 12 | 0.88192 | 0.82283 | 1.13650 | 0.85465 | 0.88192 | 0.93648 | 0.85465 |
| 13 | 0.88912 | 0.93468 | 0.82283 | 0.93648 | 1.16378 | 1.08195 | 0.88192 |
| 14 | 1.05013 | 0.99557 | 0.82283 | 0.88192 | 1.13650 | 0.93688 | 0.85465 |
| 15 | 0.90920 | 0.93648 | 0.90920 | 0.88912 | 0.93648 | 1.02285 | 0.93468 |
| 16 | 0.74100 | 0.96830 | 0.96803 | 0.90902 | 0.96830 | 0.90920 | 0.88192 |
| 17 | 0.85465 | 0.90920 | 0.85466 | 0.90922 | 0.93846 | 0.93648 | 0.90920 |
| 18 | 0.84465 | 0.90929 | 1.01830 | 1.01830 | 0.93647 | 1.02285 | 0.82283 |
| 19 | 0.90920 | 1.39108 | 0.96830 | 0.99557 | 0.90921 | 1.08195 | 0.90920 |
| 20 | 1.08195 | 1.08915 | 1.36480 | 0.90929 | 1.02285 | 0.99920 | 0.90910 |
| 21 | 1.16378 | 1.10922 | 1.10922 | 0.88192 | 0.85465 | 1.13650 | 1.08195 |
| 22 | 1.19560 | 1.13650 | 0.85465 | 0.93648 | 0.88192 | 1.02285 | 0.99557 |
| 23 | 0.90920 | 0.90920 | 0.88192 | 0.93648 | 0.99557 | 1.13650 | 1.05013 |
| 24 | 0.85465 | 1.16378 | 1.25015 | 1.16378 | 1.25015 | 1.02285 | 1.39018 |
| 25 | 1.08195 | 1.13650 | 1.27743 | 1.13650 | 1.13650 | 1.08195 | 1.16378 |
| 26 | 1.13650 | 1.42290 | 1.13650 | 1.13560 | 1.08195 | 1.42290 | 1.36380 |
| 27 | 1.47745 | 1.09195 | 1.19560 | 1.13650 | 1.13650 | 1.08195 | 1.16378 |
| 28 | 1.16378 | 1.47745 | 1.42280 | 1.36380 | 1.27743 | 1.30925 | 1.25015 |
| 29 | 1.56382 | 1.19560 | 1.42290 | 1.33652 | 1.47745 | 1.39018 | 1.70475 |
| 30 | 1.36380 | 1.16378 | 1.47745 | 1.37745 | 1.47754 | 1.45017 | 1.13650 |
| 31 | 1.13650 | 1.19650 | 1.19560 | 1.27743 | 1.22287 | 1.27743 | 1.05013 |
| 32 | 0.17275 | 1.25015 | 1.42290 | 1.45017 | 1.70475 | 1.76385 | 1.67747 |
| 33 | 1.84568 | 0.88192 | 1.13650 | 1.16378 | 1.16378 | 1.19560 | 1.08195 |
| 34 | 1.16378 | 1.10922 | 1.16378 | 1.47745 | 1.22287 | 1.13650 | 1.27743 |
| 35 | 1.13650 | 1.08195 | 1.16378 | 1.13650 | 1.16378 | 1.30925 | 1.27743 |
| 36 | 1.30925 | 1.25015 | 1.30925 | 1.42290 | 1.47745 | 1.45017 | 1.53655 |
| 37 | 1.47745 | 1.47745 | 1.42290 | 1.70475 | 1.13650 | 1.36380 | 2.04570 |
| 38 | 1.99115 | 1.70475 | 1.76386 | 1.76385 | 1.76385 | 1.46386 | 1.46386 |
| 39 | 1.10922 | 1.13650 | 1.13650 | 1.08195 | 1.02285 | 0.96830 | 1.19560 |
| 40 | 1.16378 | 0.99557 | 0.90920 | 1.10922 | 1.16378 | 1.13650 | 1.87750 |
| 41 | 1.19560 | 1.16378 | 1.02285 | 1.16378 | 1.08195 | 0.96830 | 1.02285 |
| 42 | 1.02285 | 0.88192 | 0.96830 | 0.68190 | 1.13650 | 1.30925 | 1.30925 |
| 43 | 1.16378 | 1.19560 | 1.19560 | 1.19650 | 1.13650 | 1.27743 | 1.16378 |
| 44 | 1.19560 | 1.27734 | 1.33652 | 1.10922 | 1.27743 | 1.16378 | 1.02285 |
| 45 | 1.05013 | 1.08195 | 1.13650 | 1.1360 | 1.19560 | 1.13569 | 1.08196 |
| 46 | 1.10922 | 1.19560 | 1.08195 | 1.16378 | 1.10922 | 1.05013 | 1.08195 |
| 47 | 1.08195 | 1.10922 | 1.08195 | 1.16378 | 1.13650 | 1.19560 | 1.02285 |
| 48 | 1.10922 | 0.93648 | 1.02285 | 1.02285 | 1.03285 | 1.10922 | 1.02285 |
| 49 | 1.02285 | 1.16378 | 0.99557 | 1.02285 | 1.16378 | 1.13650 | 1.10922 |

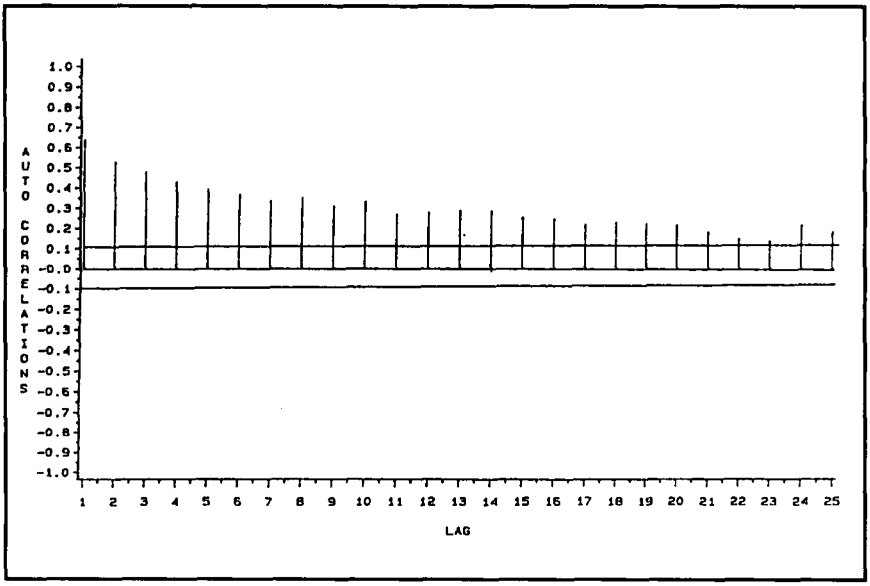


Figure 1. ACF's for the original series.

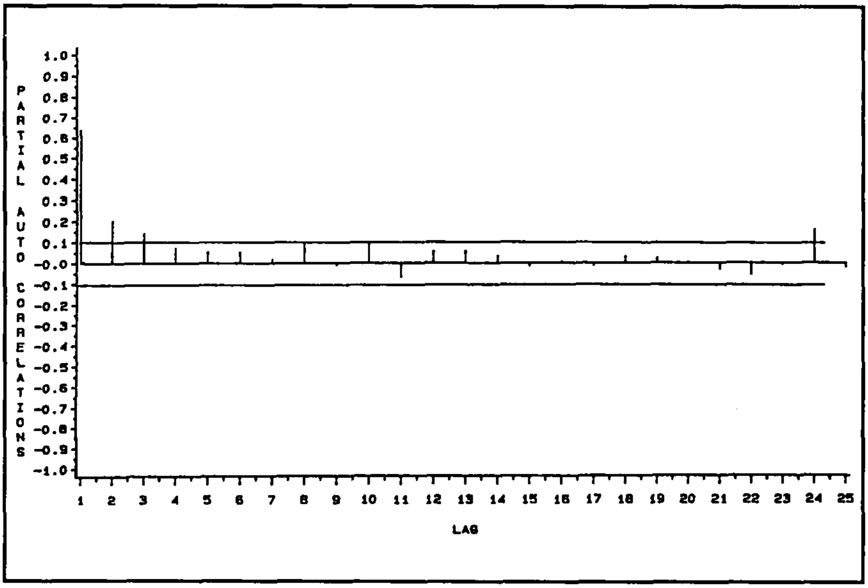


Figure 2. PACF's for the original series.

Table 2. Test Results for Equality of Means and Variances

| Test | $p$-Value | Decision |
|---|---|---|
| $H_0$: $\overline{X}_S = \overline{X}_W$ vs. $H_1$: $\overline{X}_S > \overline{X}_W$ | < 0.0001 | Reject $H_0$ for $\alpha \geq 0.0001$ |
| $H_0$: $\overline{X}_S = \overline{X}_F$ vs. $H_1$: $\overline{X}_S > \overline{X}_F$ | < 0.0001 | Reject $H_0$ for $\alpha \geq 0.0001$ |
| $H_0$: $\overline{X}_F = \overline{X}_W$ vs. $H_1$: $\overline{X}_F > \overline{X}_W$ | < 0.005 | Reject $H_0$ for $\alpha \geq 0.005$ |
| $H_0$: $S_S^2 = S_W^2$ vs. $H_1$: $S_S^2 > S_W^2$ | < 0.01 | Reject $H_0$ for $\alpha \geq 0.01$ |
| $H_0$: $S_S^2 = S_F^2$ vs. $H_1$: $S_S^2 > S_F^2$ | <0.001 | Reject $H_0$ for $\alpha \geq 0.001$ |
| $H_0$: $S_W^2 = S_F^2$ vs. $H_1$: $S_W^2 > S_F^2$ | < 0.001 | Reject $H_0$ for $\alpha \geq 0.001$ |

WINTER:
Mean = $\overline{X}_W$ = 1.03; Standard Deviation = $S_W$ = 0.19.

SPRING and SUMMER:
Mean = $\overline{X}_S$ = 1.29; Standard Deviation = $S_S$ = 0.25.

FALL:
Mean = $\overline{X}_F$ = 1.11; Standard Deviation = $S_F$ = 0.11.

(0,1,0), (0,1,1) and (0,1,2). In terms of statistical tests with respect to autocorrelations up to 24 lags of the differenced data, the significance of the moving average parameter for the incremental lag and the ACF of the residuals, there was better support for the ARIMA(0,1,1) model than for any of the other two. The model parameters were within the required bounds. Five of the 118 back forecasts were outside the forecast 95 percent confidence interval; the expected number is 5.80.

For the fall data, applying the same stages and criteria as in the previous instances, it was found that an ARIMA(0,1,1) model provided the best fit, passing all the mathematical requirements and statistical tests. Three of the 62 back forecasts were outside the 95 percent confidence interval estimates; the expected number is 3.10.

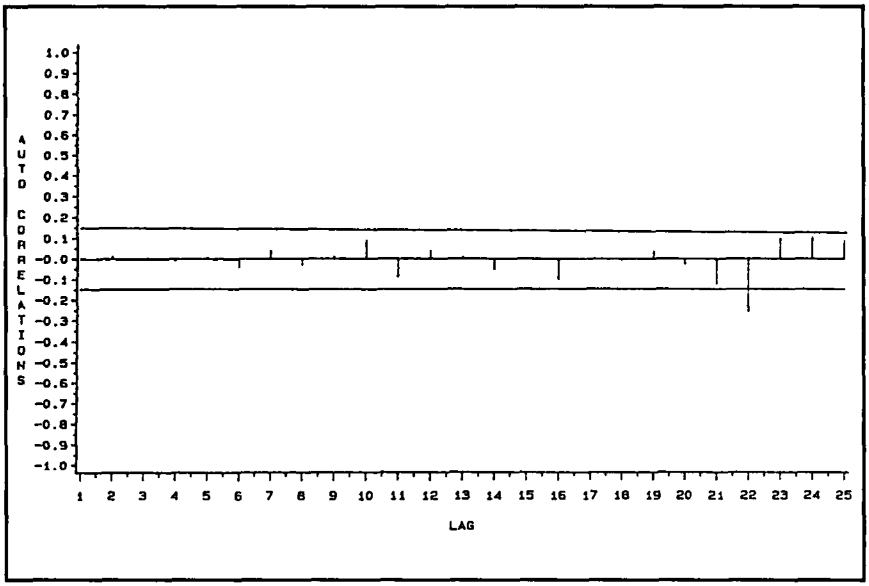


Figure 3. ACF's for the Winter Model Residuals.

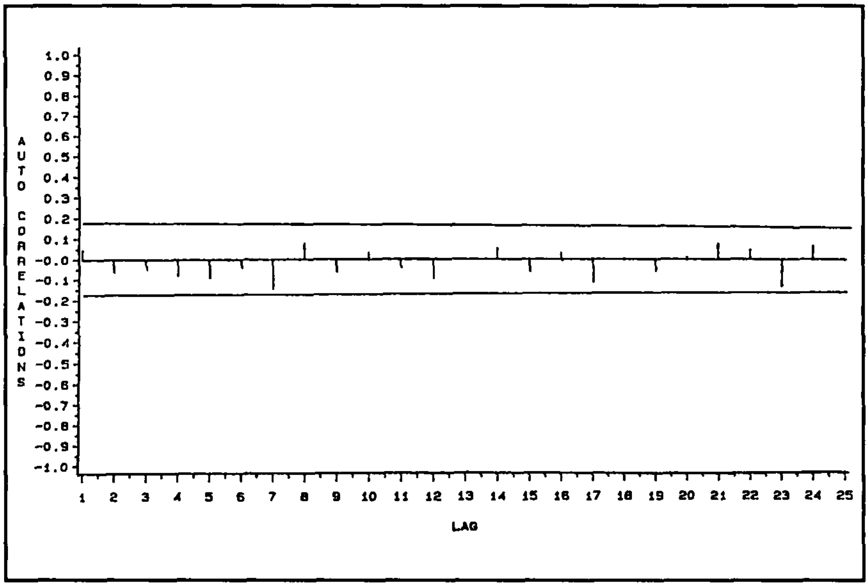


Figure 4. ACF's for the Spring Model Residuals.

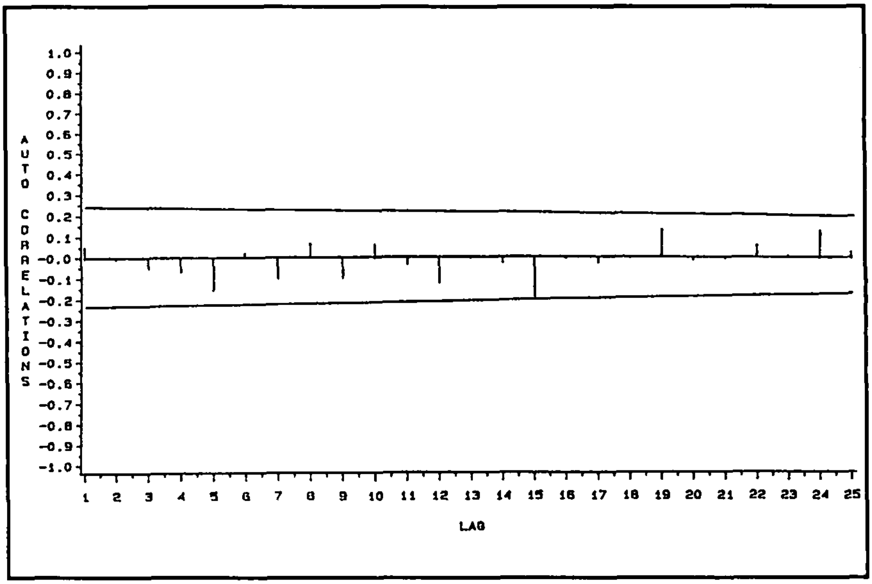


Figure 5. ACF's for the Fall Model Residuals.

The Box-Pierce Q-statistics for residuals for each of the three fitted models are shown in Table 3. The results support the hypothesis of absence of autocorrelation in the residuals. In addition, the model estimates for each of the three groups are shown in Table 4, providing instant comparison of model features, parameter estimates and the number of forecasts outside their respective confidence interval estimates.

## DISCUSSION

Given the considerable seasonal variations in temperature, humidity and water consumption needs, it becomes necessary to model each season's data separately. This analysis showed that the appropriate model for each is different.

One other justification for using the three different models instead of the annual model is provided by comparing the variance for each season with the respective variances for each of the other two seasons. The variances are 0.19, 0.25 and 0.11, respectively for winter, spring and fall; the respective sample sizes are 160, 118 and 62 for the once-differenced data. Applying the standard F-test for comparison of variances, it was found that for each of the three pairs of comparisons, the hypothesis of equality of variances is soundly rejected even at the 0.1 percent level of significance. In other words, there is no stationarity in variance, but only heteroskedasticity.

Table 3. Box-Pierce Q-Statistic for Model Residuals

| Series | Lag | Q-Statistic | $p$-Value |
|---|---|---|---|
| Winter | 6 | 0.34 | 0.9529 |
| | 12 | 3.85 | 0.9212 |
| ARIMA | 18 | 6.28 | 0.9747 |
| (0,1,2) | 25 | 27.59 | 0.1897 |
| Spring | 6 | 2.61 | 0.6243 |
| | 12 | 8.21 | 0.6082 |
| ARIMA | 18 | 11.13 | 0.8012 |
| (0,1,1) | 25 | 16.20 | 0.8466 |
| Fall | 6 | 2.46 | 0.6521 |
| | 12 | 5.84 | 0.8289 |
| ARIMA | 18 | 8.97 | 0.9147 |
| (0,1,1) | 25 | 12.52 | 0.9616 |

The $p$-values in the above table correspond to the smallest significance level at which the null hypothesis of no autocorrelation in the residuals of the given lag can be rejected, given the values of the test statistic. Thus, high $p$-values favor the null hypothesis. Or equivalently, the null hypothesis will only be rejected at significance levels greater than or equal to the $p$-values shown.

Table 4. Model Comparisons

| | | Parameter Estimates | | | Number Outside 95 Percent |
|---|---|---|---|---|---|
| Series | Model | Constant | Lag 1 | Lag 2 | C.I. |
| Winter | ARIMA(0,1,2) | –0.0004 | 0.5647 | 0.2029 | 6/160 |
| Summer | ARIMA(0,1,1) | –0.0045 | 0.4769 | — | 5/118 |
| Fall | ARIMA(0,1,1) | –0.0004 | 0.5496 | — | 3/62 |

The "Number Outside 95 percent C.I." shows the number of actuals outside their 95 percent confidence intervals estimated from the respective models, out of the total number of observations in each case.

The constant terms shown are not statistically significant from zero for any one of the models.

The mean water intake is 1.03, 1.29 and 1.11 cubic metres per day for winter, spring and fall respectively. Statistically, water intake in spring is significantly higher than fall and winter intakes, and fall water intake is significantly greater than winter water intake. Hence, in forecasting household water requirements it is advisable to model each season's requirements separately.

It must be admitted that there is some overlap in the seasons. The first week of October may be more like the last week of September, rather the rest of October itself. The cutoff dates for each season are necessarily somewhat arbitrary. This would certainly introduce some unavoidable bias in the model estimates. But, to obviate this, one would have to record the exact dates when lawn watering begins and ends for each household, the exact dates when significant changes occurred in climatic conditions resulting in significant changes in water use patterns for a given household and so on. Such data are not usually easily collected; and even if they are, generalizations based on such data may not be valid.

As a final check of the model adequacy, each model was run by omitting some data points and then the values forecast by the models were compared against the corresponding actuals. Thus, the Winter ARIMA (0,1,2), the Spring ARIMA (0,1,1) and the Fall ARIMA (0,1,1) models were estimated by dropping each of their respective last twelve observations. Then, the respective forecasts were used to estimate 95 percent confidence intervals for each of the omitted observations under each model. It was found that in each case, all the actual values were well within their respective confidence interval estimates. Thus, the choice between one comprehensive annual model and three models, one each to account for the regular variations in water use patterns boils down to the causal justifications for each model. The heteroskedasticity found in the annual data and the adequacy of the models passing all tests lead us to conclude that the three models, corresponding approximately with the seasonal changes and observed water consumption patterns, are a better choice than a single annual model.

Effective water management in municipal areas requires a reasonably accurate knowledge of water use throughout the year. This is especially true of water use in residential dwellings where individual water use activities produce an intermittent flow of wastewater which can vary widely in volume. Detailed data on such water use are not only necessary to develop effective designs of on-site wastewater disposal systems, but also to plan water conservation and waste load reduction strategies. The significantly enhanced water use in spring and summer (June-September) reflects the lawn sprinkling use. Seasonal variations were not very marked with respect to other uses. Water conservation and water rationing measures, if needed, should therefore be directed to lawn sprinkling in the summer; year-round, they have to be directed towards other uses such as dishwashing, reduced capacity of water closet flush tanks and lowered shower use through water saving fittings. Thus, the type of data and analysis presented in this article can be used in making reasoned and sensible decisions for water conservation. In the case of onsite wastewater disposal systems, maximum water use less the lawn sprinkling use should be examined to determine the adequacy of design of both the septic tank and the subsurface disposal system which are normally based on average flows. Further, better long-term forecasting of water needs can be carried out by paying attention to the time series properties of water intake and to any significant deviations from the mean if they are found to persist over time.

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