IDENTIFYING THE RELATIONSHIPS BETWEEN URBAN WATER CONSUMPTION AND WEATHER VARIABLES IN SEOUL, KOREA

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Abstract: As anthropogenic climate change threatens the reliability of urban water supplies, it is essential to build understanding of the relationships between weather and water consumption. We used daily and monthly data from 2002 to 2007 to conduct a statistical analysis of how seasonal water use in Seoul, South Korea is affected by weather variables. The Pearson, Kendall, and Spearman tests indicated that all weather variables were significantly correlated with per capita water use at most timescales, with mean, minimum, and maximum temperatures and daylight length positively correlated, and precipitation, wind speed, relative humidity, and cloud cover showing an inverse relation with water use. Once the influence of maximum temperature is controlled, water consumption is only significantly associated with wind speed and daylight length, as indicated by the partial correlation coefficient values. Ordinary least square (OLS) regression models explain between 39 and 61% of the variance in seasonal water use, indicating that approximately one-third to two-thirds of the variation is due to weather variables alone. Daily water consumption in July increases up to 4 liters per person with a one degree increase in maximum temperature. Significant improvement of the modeling of seasonal water use was achieved by developing autoregressive integrated moving average (ARIMA) models, which account for autocorrelation in the time series and explain up to 66% of the variance in water use. Our results indicate that weather plays a significant role in determining water consumption in Seoul, and that has important implications for management of urban water resources under potential future climate change. [Key words: temperature, wind speed, water consumption, regression, ARIMA, Seoul.]

INTRODUCTION

As global climate changes and urban populations continue to grow, water resources in many world cities are likely to experience increasing stress from diminished water supply and greater demand (Bates et al., 2008). One world city whose water resources may be affected by climatic and socioeconomic changes is Seoul, South Korea. According to recent research by the Meteorological Institute of Korea (CRL, 2009), the rate of temperature change in Korea between 1906 and 2005 (1.7° C) is higher than the world mean (0.74° C), suggesting that Korea will be much warmer than the rest of the world if this trend continues in the future. In addition, as its metropolitan areas are projected to grow further, urban-heat-island effects will be enhanced (Kim and Baik, 2005; Um et al., 2007), inducing additional water demand. In reality, the temperature increase of Seoul for the same period (1906–2005) is 2.4° C, 0.7° C higher than the country-wide mean. A North American case study shows that 1° C increase in temperature induced 1973 liters of additional

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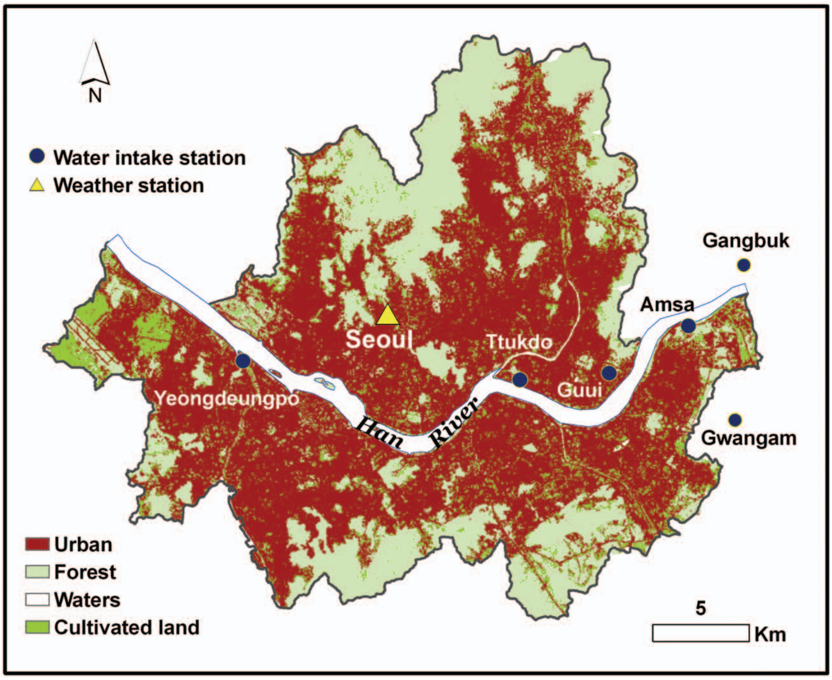

Fig. 1. Land use and the locations of water intake stations for Seoul.

water consumption per single family household in June in Phoenix, Arizona (Guhathakurta and Gober, 2007).

Although there have been several studies investigating the role of weather and climate variables in municipal water consumption (e.g., Perry, 1981; Maidment and Parzen, 1984; Maidment et al., 1985; Maidment and Miaou, 1986; Miaou, 1990; Jowitt and Xu, 1992; Kenward and Howard, 1999; Balling and Gober, 2007; Balling et al., 2008; Ghiassi et al., 2008), most studies have focused on a limited number of climatic variables. Previous studies used maximum and minimum temperatures and precipitation as explanatory variables to estimate water consumption. In addition, the interactions among different weather and climate variables that influence water use are not well understood. We conducted a statistical analysis of the relation between observed climate and municipal water use in Seoul for the years 2002 to 2007, as a preliminary step in establishing the extent to which water use is affected by weather and climate and what weather and climate variables are most deterministic.

DATA AND METHODS

The Korean Meteorological Agency provided daily weather variables for Seoul for the years 2002 to 2007 (Figs. 1, 2A, and 3). The weather station (station number 108) is located in Seoul and is considered to be a representative station with a

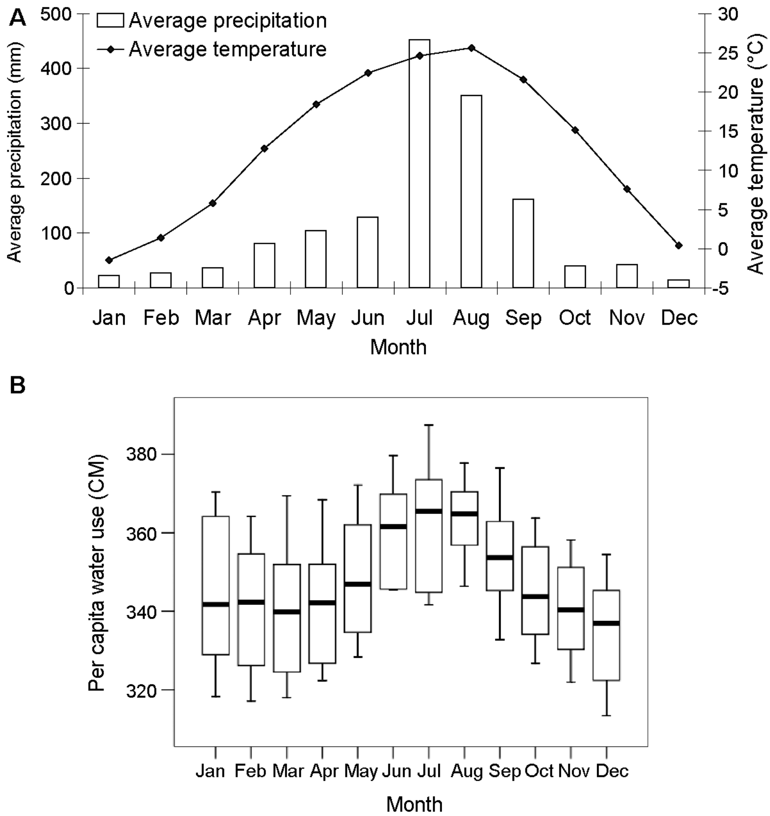

Fig. 2. A. Average monthly temperature and precipitation for 2002–2007 in Seoul, South Korea. B. Per capita municipal water use for 2002–2007 in Seoul, South Korea.

relatively long term record. Daily municipal water production data were obtained from the office of waterworks in Seoul (Office of Waterworks, 2009; Fig. 2B). While the water use data were separated into different geographic areas and sectors, we considered only the total water use for all sectors in the entire city. Although temperature and precipitation data were available for more stations, we included only one weather station with a reliable continuous record of additional weather variables. This level of spatial detail was appropriate because we do not have finer spatial resolution water use data at the daily scale. While spatial variability may be important in explaining variation in water consumption, in this research we chose to focus instead on including the largest number of different weather variables to determine which are most significant in determining patterns of daily water use. As shown in Figure 3, there are no significant trends in summer temperature and precipitation during the study period.

Because we believe that water use may be more sensitive to weather variables during the summer, we examined only the four summer months (June through

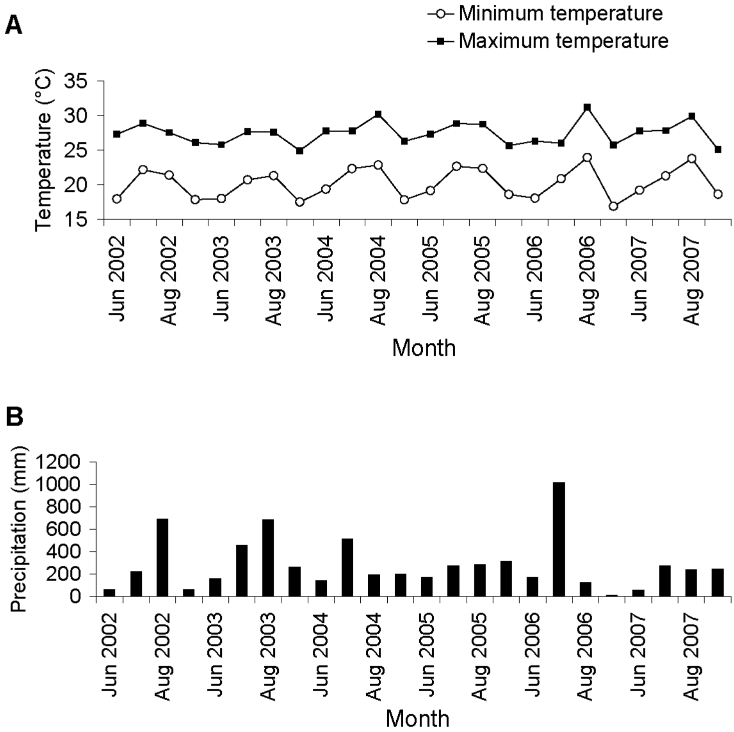

Fig. 3. Average monthly minimum and maximum temperature (A) and total monthly precipitation (B) for Seoul, South Korea, June 2002 to September 2007 (June through September only).

September), both separately and aggregated as a season. To separate climatically dependent seasonal use from indoor base use, we subtracted the average December use (the month of lowest use) from each summer month's use, yielding the seasonal use for each month. Although this method of calculating seasonal use is imprecise, it is the best available option, inasmuch as the data provided by the waterworks office do not differentiate indoor from outdoor use. Similar approaches to estimating seasonal water use, in which the base use is assumed to be equivalent to the use during the months of lowest water consumption, were used in Maidment et al. (1985), Zhou et al. (2000), and Syme et al. (2004). Outdoor municipal water use in Seoul is primarily for landscape irrigation. Because of the predominance of apartment-style housing, other outdoor uses of water, such as car washing and filling private swimming pools, are not significant in Seoul. We do not, however, have sufficient data to estimate allocations of water to different outdoor activities.

The weather variables we included in our analysis were average temperature (°C), minimum temperature (°C), maximum temperature (°C), precipitation (mm), wind speed (m/s), relative humidity (%), daylight length (hrs), and cloud cover (%). Total water use was measured in cubic meters. We averaged or summed initial daily values to obtain monthly values. For all weather and water use data, we performed summary statistics, obtaining the mean, standard deviation, and kurtosis for descriptive purposes. We checked all data for temporal autocorrelation and used the Kolmogorov-Smirnov test for normality. To attempt to correct for temporal autocorrelation, we developed ARIMA models using EasyReg software for all variables and performed further analysis (Pennsylvania State University, 2008). Non-normal data were logarithmically transformed for use in further analysis. To determine the direction and strength of relations between each of the weather variables and water use at the different time scales, we performed three tests of correlation. The first was the parametric Pearson's correlation coefficient for normal data; the other two were the non-parametric Kendall's tau and Spearman's rho. Finally, in order to evaluate the extent to which variation in water use can be explained by weather and which variables had the most explanatory power, we performed a multiple ordinary least square (OLS) linear regression analysis, using a stepwise selection procedure, at each timescale.

RESULTS

Descriptive Statistics

Table 1 presents summary statistics for all weather and water use variables for individual summer months and the entire summer season. Temperatures are highest in August. July is the summer month with highest precipitation, relative humidity, and cloud cover, and shortest daylight length. (In this study, "daylight length" refers to the clear-sky period during the day when solar insolation is not obscured by cloud cover, fog, haze, or smog.) The autocorrelation coefficients for all variables are significant at all timescales, indicating that these data have a high level of temporal autocorrelation. The only exceptions are precipitation in June, July, and September, and wind speed in June.

According to the Kolmogorov-Smirnov test of normality, most summer weather and water use variables are normally distributed. The exceptions are precipitation ($z = 9.864$), wind speed ($z = 2.272$), and cloud cover ($z = 3.960$), which all have skewed distributions as a result of numerous zero values. We logarithmically transformed the non-normal variables to allow for linear analysis.

Correlation between Weather Variables and Water Use

Table 2 displays the Pearson correlation matrix for the aggregated summer weather and water use variables. All variables are significantly correlated with one another except average temperature and wind speed, minimum temperature and precipitation, and wind speed and daylight length. All the temperature variables and daylight length are positively associated with water use, while precipitation, wind speed, relative humidity, and cloud cover are negatively associated (Fig. 4). The significance of these correlations was confirmed with the non-parametric Kendall and Spearman tests (not shown). We also performed a partial correlation analysis of the relation between the weather variables and water use while controlling for maximum temperature. The only significant partial correlations are for wind

Table 1. Summary Statistics for Daily Weather and Water Use Variables

Statistic	Variable	June	July	August	September	Summer	Annual
Mean	Mean temperature (°C)	18.61	24.43	25.51	21.45	23.48	12.94
	Minimum temperature (°C)	27.02	21.67	22.6	17.88	20.22	9.25
	Maximum temperature (°C)	4.15	27.81	29.18	25.62	27.43	17.21
	Precipitation (mm)	2.15	14.73	11.88	6.02	9.26	4.17
	Wind speed (m/s)	65.31	2.17	2.17	1.98	2.12	2.28
	Relative humidity (%)	4.99	77.28	74.22	68.34	71.36	62.01
	Daylight length (hrs)	9.97	2.48	3.6	4.35	3.84	4.93
	Cloud cover (%)	0.36	76.68	68.27	58.24	65.9	48.91
	Seasonal water use (m^3 per person per month)	124.39	148.11	152.73	59.44	121.65	348.2
Standard deviation	Mean temperature (°C)	24.43	2.31	2.33	2.15	2.76	9.9
	Minimum temperature (°C)	21.67	1.96	2.25	2.35	2.91	9.97
	Maximum temperature (°C)	27.81	3.06	3.04	2.61	3.25	10.1
	Precipitation (mm)	14.73	35.46	28.32	16.83	25.45	16
	Wind speed (m/s)	2.17	0.77	0.88	0.85	0.78	0.8
	Relative humidity (%)	77.28	9.83	9.41	11.12	12.33	14.84
	Daylight length (hrs)	2.48	3.01	3.61	3.63	3.78	3.68
	Cloud cover (%)	76.68	22.78	26.5	30.29	28.79	32.17
	Seasonal water use (m^3 per person per month)	148.11	19.85	14.79	18.64	17.68	19.28
Autocorrelation coefficient	Mean temperature (°C)	0.558	0.621	0.743	0.615	0.782	0.971
	Minimum temperature (°C)	0.63	0.678	0.715	0.637	0.857	0.97
	Maximum temperature (°C)	0.44	0.506	0.609	0.437	0.591	0.95
	Precipitation (mm)	0.099*	0.158*	0.301	–0.01*	0.207	0.238
	Wind speed (m/s)	0.157**	0.269	0.454	0.497	0.4	0.408
	Relative humidity (%)	0.659	0.469	0.542	0.504	0.644	0.593
	Daylight length (hrs)	0.452	0.28	0.451	0.315	0.445	0.329
	Cloud cover (%)	0.507	0.441	0.545	0.408	0.525	0.457
	Seasonal water use (m^3 per person per month)	0.813	0.802	0.704	0.768	0.798	0.902

*Autocorrelation not significant at 0.01 level.
**Autocorrelation not significant at 0.05 level.

Table 2. Pearson Correlation Matrix for Summer Weather and Water Use Variables

	Min Temp	Max Temp	Precip	Wind	Relative Humidity	Daylight Length	Cloud Cover	Per Capita Water Seasonal Water Use	Partial Correlation[a]
Av Temp	0.87**	0.91**	–0.17**	0.02	–0.13**	0.16**	–0.21**	0.41**	0.009
Min Temp		0.63**	0.01	0.14**	0.23**	–0.12**	0.16**	0.28**	0.002
Max Temp			–0.29**	–0.08*	–0.40**	0.38**	–0.49**	0.45**	
Precip				0.11**	0.48**	–0.29**	0.36**	–0.15**	–0.028
Wind					0.08*	–0.06	0.18**	–0.22**	–0.208**
Relative Humidity						–0.58**	0.69**	–0.15**	0.029
Daylight Length							–0.69**	0.10**	–0.085*
Cloud Cover								–0.23**	–0.017

[a]Water use, controlled for max temp.
*Significant at 0.05 level.
**Significant at 0.01 level.

speed and daylight length. These results indicate that the influence of these two variables is significant independently of maximum temperature. The best fit for the data is linear only in the case of minimum temperature. For average and maximum temperature, the best-fit equation is exponential, for wind speed it is logarithmic, and for the remaining variables it is a second-order polynomial.

Factors Affecting Water Use

We developed OLS regression models to explain how much variations in water use are explained by weather variables for each timescale, entering all variables in a stepwise procedure. In order to detrend the time series, we used anomalies from the mean rather than the raw water use and weather values. Table 3 shows the results of the stepwise multiple linear regression analysis for weather variables at all timescales. The R^2 values for the final models range from 0.389 for August to 0.613 for July. In June, the most important explanatory variables are maximum temperature, which has a positive relation with water use, and daylight length, which has a negative effect. In July, maximum temperature is directly related to water use. In August and September, the most important variables are maximum temperature, which has a positive effect on water use, and wind speed, which has an inverse relationship. For the aggregate summer season, maximum temperature has a positive relationship with water use, and wind speed and daylight length have an inverse relationship with water use. Table 4 includes the multicollinearity statistics

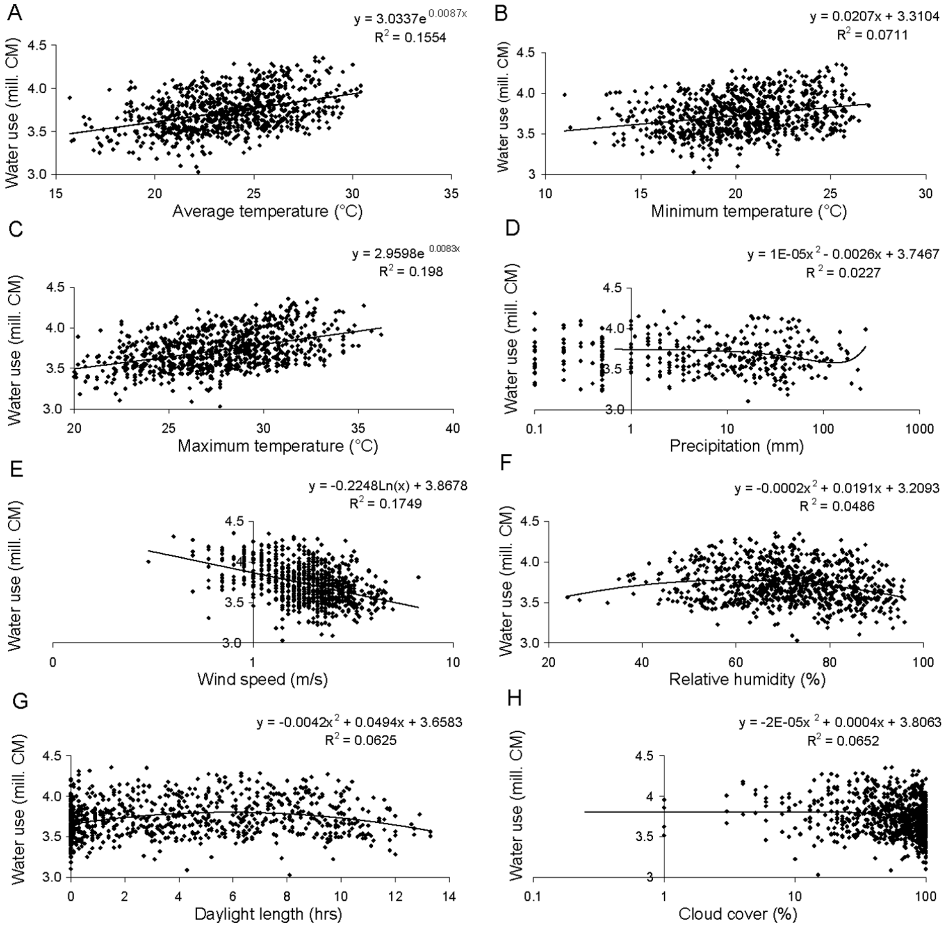

Fig. 4. Summer daily water use and (A) mean temperature, (B) minimum temperature, (C) maximum temperature, (D) precipitation, (E) wind speed, (F) relative humidity, (G) daylight length, and (H) cloud cover, in Seoul, South Korea, 2002–2007.

for the OLS stepwise regression models. According to the tolerance and variable inflation factor (VIF), multicollinearity is not a problem for most variables.

In addition to the OLS models, we also developed autoregressive integrated moving average (ARIMA) models for each timescale. These models account for the autocorrelation in the water demand time series by using the previous day's water use as an independent variable. ARIMA models are characterized by the form ARIMA (p, q) where p represents the number of autoregressive terms (AR) and q represents the size of the moving-average window (MA) (Huang et al., 2004). The process of specifying an ARIMA model entails first identifying a model type and then estimating the parameters. We iteratively fitted our time series with various ARIMA types and evaluated their fit based on the Akaike, Hannan-Quinn, and Schwarz information criteria. Through this process, we selected an ARIMA (2,1)

Table 3. Final Stepwise Linear Regression Models for Weather and Water Use Variables

Timescale	Variables included	Unstandardized coefficient	Standardized coefficient	t	p	Final R^2
June	Maximum temperature (°C)	2.039	0.425	6.252	< .01	
	Daylight length (hrs)	–0.567	–0.159	–2.332	< .05	0.437
July	Maximum temperature (°C)	3.980	0.613	10.515	< .01	0.613
August	Wind speed (m/s)	–4.960	–0.296	–4.343	< .01	
	Maximum temperature (°C)	1.147	0.236	3.548	< .01	0.389
September	Maximum temperature (°C	2.431	0.340	5.108	<. 01	
	Wind speed (m/s)	–6.646	–0.304	–4.566	<. 01	0.463
Summer	Maximum temperature (°C)	2.538	0.467	13.371	<. 01	
	Wind speed (m/s)	–4.273	–0.189	–5.839	< .01	
	Daylight length (hr)	–0.412	–0.088	–2.522	< .05	0.493

Table 4. Multicollinearity Statistics for OLS Stepwise Regression Models

Timescale	Variables included	Tolerance	VIF
June	Maximum Temperature (°C)	0.002	1.996
	Daylight Length (hrs)	0.953	0.007
July	Maximum Temperature (°C)	0.006	0.315
August	Wind Speed (m/s)	0.037	2.895
	Maximum Temperature (°C)	0.979	0.100
September	Maximum Temperature (°C)	0.024	2.885
	Wind Speed (m/s)	0.017	1.995
Summer	Maximum Temperature (°C)	0.031	1.993
	Wind Speed (m/s)	0.904	2.907
	Daylight Length (hrs)	0.071	3.500

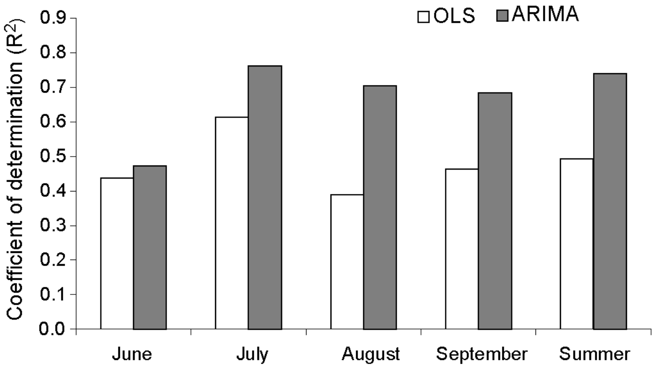

Fig. 5. Comparison of OLS and ARIMA model R^2 values.

model, with 2 autoregressive lags (AR) and a moving average window of 1 (MA). The general form of our ARIMA models is:

$$Y_t = \mathrm{I}_p(B)Z_t + Y_{t\text{-}1} + X,$$

where Y_t = per capita seasonal water use at time t; $\mathrm{I}_p(B)Z_t$ = the series of the autoregressive component of order p of the time series Z_t; $Y_{t\text{-}1}$ = per capita seasonal water use at time t-1; and X = the set of all independent weather variables. The ARIMA models significantly improve each model's fit compared to OLS models, explaining between 47 and 76 percent of the variance in seasonal water use (Fig. 5). This reflects the aforementioned substantial autocorrelation in the demand time series.

DISCUSSION

Many municipalities are concerned about the reliability of water supplies in light of future climate change and population growth (Morehouse et al., 2002; Ruth et al., 2007; O'Hara and Georgakakos, 2008). In this study, we find that between 39% and 61% of Seoul's seasonal water use is determined by weather variables. This sensitivity is significant enough that changes in these weather variables, such as higher summer temperatures or changing precipitation patterns, will potentially alter patterns of water use in Seoul.

Through our correlation analysis, we discovered that most of the weather variables were strongly correlated with water use, particularly in summer. Not surprisingly, higher temperatures, especially maximum temperatures, were associated with higher levels of water use, which has been found in other previous studies (Balling et al., 2008). As shown in Table 3, a one degree increase in maximum temperature yields an increase of 2 to 4 liters of daily, per capita water consumption in Seoul, with the highest coefficient in the month of July. The relatively low coefficient values are associated with the rainy season and frequent summer storms in both months.

Predictably, precipitation and water use had an inverse relationship during the summer months. It is also logical that longer daylight length and less cloud cover were associated with higher water use. The inverse relationships of wind speed and relative humidity with water use may be explained by less water being used on stormy days in summer, which are likely to be windy and humid. The direction of the significant correlations is therefore intuitive. These correlations indicate that there are significant relations between summer weather and water use in Seoul that are worthy of further exploration.

Daylight length and wind speed were two weather variables that we found to be highly significant in explaining patterns of water use in Seoul. As shown in the correlation matrix, days of higher winds are likely to have more cloud cover, reducing diurnal temperature, which is likely to contribute to less water consumption. These variables have not been commonly used in previous studies examining the relation between weather and water use. Our partial correlation analysis indicates that the significance of these variables remains even when maximum temperature is controlled for, suggesting that they are independently related to water use. One implication of our research is that inclusion of these variables in municipal water use models, in addition to the more traditional temperature and precipitation variables, may improve the explanatory power when reliable data are available.

The stepwise linear regression models of the non-lagged variables explained less than half of the variance in water use in some months, indicating that non-climatic factors may be significant in determining water use in Seoul. Inclusion of temporal autocorrelation through the ARIMA models, however, significantly improved the model fit. We will attempt to include socioeconomic factors in future analyses in order to gain a fuller picture of the determinants of water use. In the regression models, the most consistently significant variables were maximum temperature, wind speed, and daylight length, indicating that it may be beneficial to focus on these variables in further analyses.

In this study, we focused solely on weather influences on seasonal water demand. Water use is, however, dependent on other factors as well, including pricing, conservation measures, and demographics (Kenney et al., 2008; Cooley and Gleick, 2009). It is likely that these variables would explain some of the remaining variance in our regression models. Examination of rate structures and conservation programs would be of particular interest, as these factors, unlike climate and population, are within the control of the water utility. Gutzler and Nims (2005) found that the implementation of a major conservation program in 1994 sharply reduced the non-climatically sensitive base use in Albuquerque, so that seasonal use now accounts for a greater proportion of total demand. This finding indicates that water utilities can successfully reduce demand through conservation programs, an approach that may become increasingly necessary under climate change and population growth. In Seoul, per capita water consumption also has declined since the late 1990s (Chang et al., 2007), suggesting that the water conservation program has been effective.

CONCLUSIONS

This study examined the relation between daily weather variables and water use in Seoul. Similar to previous studies, we found that maximum daily temperature is a good predictor of seasonal water consumption. We also found that wind speed is a good predictor of seasonal water use in a humid temperate climate, a less well documented finding in the literature. It is likely that higher wind speed increases evaporation of water, which induces a cooling effect and thus decreases daily water consumption. Together, these variables explain between 39 and 61% of the variations in seasonal water use in Seoul. The ARIMA model that takes into account temporal autocorrelation significantly improves the model prediction. We have found sufficiently strong evidence of significant relations that further analysis is warranted. Further development of climatically based regression models will allow us to project potential changes in seasonal water demand in Seoul as a result of climate change. Eventually, we plan to also incorporate non-climatic variables such as sociodemographic or structural variables (Zhang and Brown, 2005) that vary over space to provide our models greater explanatory power. A spatially explicit approach to identifying the determinants of water use has been introduced in North American case studies (e.g., Wentz and Gober, 2007; Balling et al., 2008; Franczyk and Chang, 2009). As climate changes and population continues to grow in cities such as Seoul, it is essential to understand how these trends may affect municipal water use in the future.

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