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Evaluating the Impact of Meteorological Factors on Water Demand in the Las Vegas Valley Using Time-Series Analysis: 1990–2014

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Abstract: Many factors impact a city's water consumption, including population distribution, average household income, water prices, water conservation programs, and climate. Of these, however, meteorological effects are considered to be the primary determinants of water consumption. In this study, the effects of climate on residential water consumption in Las Vegas, Nevada, were examined during the period from 1990 to 2014. The investigations found that climatic variables, including maximum temperature, minimum temperature, average temperature, precipitation, diurnal temperature, dew point depression, wind speed, wind direction, and percent of calm wind influenced water use. The multivariate autoregressive integrated moving average (ARIMAX) model found that the historical data of water consumption and dew point depression explain the highest percentage of variance (98.88%) in water use when dew point depression is used as an explanatory variable. Our results indicate that the ARIMAX model with dew point depression input, and average temperature, play a significant role in predicting long-term water consumption rates in Las Vegas. The sensitivity analysis results also show that the changes in average temperature impacted water demand three times more than dew point depression. The accuracy performance, specifically the mean average percentage error (MAPE), of the model's forecasting is found to be about 2–3% from five years out. This study can be adapted and utilized for the long-term forecasting of water demand in other regions. By using one significant climate factor and historical water demand for the forecasting, the ARIMAX model gives a forecast with high accuracy and provides an effective technique for monitoring the effects of climate change on water demand in the area.

Keywords: climate change; urban water demand; long-term forecasting; time-series analysis; ARIMAX; transfer function; semi-arid region; Las Vegas

1. Introduction

The Las Vegas Valley, located in the arid southern Nevada region, has had an increasingly growing population in the past 15 years, with limited water resources. The area has also experienced a prolonged drought, spanning fifteen years from 2000 to 2014, and faces unique challenges in meeting its future water needs [1]. The uncertainty of water resources is an important issue for the community due to climate change and its impacts on precipitation levels and spring runoff from the melting snow in the mountains [1]. The water demands keep increasing because of the increasing population and the hydrological response. An example of a hydrological response is drought, which puts additional stress on water utilities. Because of these circumstances, valley water managers and planners require accurate depictions of water demand over medium and long-term forecasts to predict the water demand due to uncertain events that might affect water availability; additionally, this assists in planning for the needs of future investments and the infrastructure of water utilities.

The availability of water continues to be a critical issue in the valley, as is evident from the continuous drought from 2000 to 2014, which has affected its precipitation patterns due to climate change [2]. Subsequently, the elevation of Lake Mead, the major water supply for the Las Vegas area, dropped to a historic low level of 1081 feet in 2010 [2]. As a result, the Southern Nevada Water Authority (SNWA) initiated a drought plan and implemented effective conservation programs in the mid-1990s [3].

For the planning, management, and development of water supply systems, the characteristics of water demand, together with uncertainties in natural phenomena, have caught the attention of many water resource researchers [4–17]. Kenney et al. [7] described that water consumption is mainly composed of three main factors: (1) socioeconomic factors, such as population distribution and sizes of homes and lots; (2) climate factors, such as air temperature, precipitation, and percent of humidity; and (3) policy factors, such as the cost of water utilities, regulations, and conservation programs. This study considers population, policy, and climate as factors in the modeling of water demand.

Due to the seasonal characteristics of water consumption and the complex stochastic and dynamic characteristics of external influences, such as climate systems and social and economic activities, it is challenging to develop appropriate models for accurate predictions of water consumption. There are a few previous studies on water demand modeling undertaken in Las Vegas [13–17]. Trabia et al. [13] used multiple linear regression to assess water use by several water demand related components (e.g., landscaping, showers, pools, etc.). Belsford et al. [14] applied the log transform multiple regression method for decomposing multiple drivers of consumption using a dataset of neighborhood water consumption, home infrastructure characteristics, and vegetation in Las Vegas. Tchigriaeva et al. [15] developed and estimated a random effects model using five years of monthly water use at the household level with four categories of factors that influence residential irrigation water demand in Las Vegas. These four categories of factors are exogenous factors, pricing policies, voluntary conservation incentives, and mandatory conservation regulations. Exogenous factors include precipitation, temperature, wind speed, household characteristics, and economic trends. Boulos et al. [16] used a hydraulic-based model and a water network decision support system to forecast real-time water demand in Las Vegas. The real-time integration of supervisory control and data acquisition (SCADA) data was used as a boundary condition (e.g., tank water levels) and operational status (e.g., pump speeds or on/off status, valve settings) in the network model [16]. Lott et al. [17] used a mix-effected model (fix and random model), which includes independent variables such as the number of bedrooms, age of the house, yard size, monthly income, water price, a one-month lag of average temperature, days of precipitation per billing cycle, and average wind speed per billing cycle. These water demand models, except for Boulos's real time hydraulic-based model, contain categorized components that describe characteristics of residential water demand, and include one or more weather variables to control for the influence of weather on the seasonality of residential water use.

As mentioned above, there are multiple demand-related variables, and those factors can be and often are interrelated. Moreover, water conservation practices and the availability of water strongly influence urban water demand [9,14,15]. This demand can be controlled by adoption of a water conservation plan. For example, Las Vegas first initiated a conservation plan in 1995 [1]. Once the goal was achieved, an additional water conservation plan was implemented to sustain the required per capita water supply. Since 1999, SNWA has formulated a new conservation plan every five years. During this period, the SNWA reviews its conservation plan efficiency at the one-year mark and makes subsequent changes as required [3]. The currently implemented conservation measures in Las Vegas include: water pricing such as increasing block rates and water-waste fees, incentives such as water smart landscape rebate programs, rebate coupons, water efficient technologies, single-family indoor retrofits, regulation such as land-use codes and water-use ordinances, and education such as public-education outreach programs and demonstrations of water-efficient gardens [3]. As a result of this additional conservation plan, the SNWA projects a reduction in total demand from 199 gallons per capita per day (GPCD) (753 liters per capita per day (LPCD)) in 2035 to 190 GPCD (719 LPCD) in 2055 [1]. Between 1996 and 2007, Las Vegas's trajectory of reduced water consumption rates was

significantly lower. The average consumption during this period for an individual household declined by 55%, while that of the population increased by 63%. These results exhibit strong evidence of the success of Las Vegas's policies [14].

In this paper, we develop and test a model that does not isolate those effects (unlike the previous studies) but uses the historical water demand data to represent all of those factors that affect water demand in the region. The historical water demand data contains accumulated information that is a result of water demand related factors in the past, which are used in this paper's model to be independent variables for predicting future water demand.

For residential water demand, variation happens mostly in summer where outdoor water use and irrigation account for the main uses. Water losses due to evapotranspiration are the reasons for consumptive use for outdoor and irrigation activities. These activities vary based on climate factors, such as temperature, radiation, percent of humidity, dew point temperature, and wind speed [18,19]. Thus, seasonality and climate are also considered in this study's model.

In general, outdoor and irrigation water demands are influenced by the amount of rainfall and temperature. For Las Vegas or semi-arid areas where there is minimal rainfall, the outdoor water demand is mainly influenced by the evapotranspiration process. This process is represented by evapotranspiration-related climate factors, such as dew point depression, diurnal temperature, average temperature, and wind speed. We assume that these climate factors have a minimal effect on indoor water use. This study's model will be tested for the influence of precipitation and each evapotranspiration-related climate factor's impact on water demand.

A time-series model has been introduced into the time pattern water consumption model, which can capture long-term trends, seasonal variation, autocorrelation, and random shocks that perturb the water demand. Maidment et al. [4] and Tiwari et al. [20] use a time-series model to describe monthly water use. Maidment et al. [4] described that water consumption is mainly composed of four components: (1) a long-term trend due to policies and socio-economic variables, (2) seasonal variation from the annual cycle of weather, (3) autocorrelation due to perpetuation of past water use variation, and (4) climatic correlation due to rainfall, evaporation, and air temperature. Thus, a time-series approach has an intuitive potential in explaining the characteristics of water demand.

In order to accomplish water resource planning for efficient water management in the Las Vegas metropolitan area, the purposes of this study are: to develop a prediction model for mid- to long-term water demand, to consider the relationship between past water demand and local climate characteristics, and to identify the key climate factors impacting residential water consumption. Thus, our empirical model of residential water demand in the Las Vegas metropolitan area accounts for both seasonal and climatic impacts by using long-term historical water demand and climate data.

The final model for each climate factor results from the curve fitting of water demand among comparative transfer function with noise (ARIMAX) models. The 60-month water demand forecast is calculated from each of the best-fit ARIMAX models and the ARIMA (no climate input) model. The impact of the climate factor on water demand can be determined by improving the accuracy performance of the ARIMAX model from the ARIMA model.

This study is unique, because limited research has been conducted to address the impact of climatic factors on water demand modeling [5,8,11,12]. Very few studies in the past have applied principal components as independent variables for water demand prediction to manage the issue of multicollinearity among the independent variables [9,11]. Our study applies a principle component technique to combine the inter-related climate factors into a single index factor for the investigation of cumulative underlying climate effects on water demand. To determine the most influential climatic factors, this study tested nine meteorological factors and two climatic principle component indexes for their effects on long-term (25-year) water demand using ARIMAX (transfer function-noise models). Furthermore, none of the previous studies have developed ARIMAX equations specifying the number of lags on variables (for both deterministic and stochastic terms) to forecast monthly water demand. Additionally, time-series modeling has been predominately been used for short-term

forecasting [5,9,21,22], but this study could be utilized for medium- to long-term forecasting. Lastly, we simulate water demand from the ARIMAX equations to estimate the sensitivity of water demand due to climate change impact. The major contribution of this paper is not only that it addresses the influence of climatic factors on residential water demand in the semi-arid metropolitan area of Las Vegas, but also that it provides a long-term forecasting model for sensitivity tests of the effects of climate change on water demand in the area. Moreover, these ARIMAX models can be adapted to other regions to improve their water planning and conservation policies.

2. Study Area

Las Vegas is located in the southeast corner of Nevada in the southwestern part of the United States, as shown in Figure 1. The Las Vegas metropolitan area is one of the fastest-growing metropolitan areas in the United States, gaining more than one million new residents in the past 15 years, and totaling about 2 million residents in 2010 [23]. Located in a desert basin with no rivers, Las Vegas also receives less than five inches of rainfall each year, and has temperatures that regularly exceed 100 degrees Fahrenheit in the summer. The drainage basin extends approximately 65 km (40 miles) from the Spring Mountains in the west to Lake Mead in the southeast [24]. The city's major source of water is Lake Mead, which accounts for 90% of its water supply, while the rest is drawn from groundwater in the basin [3].
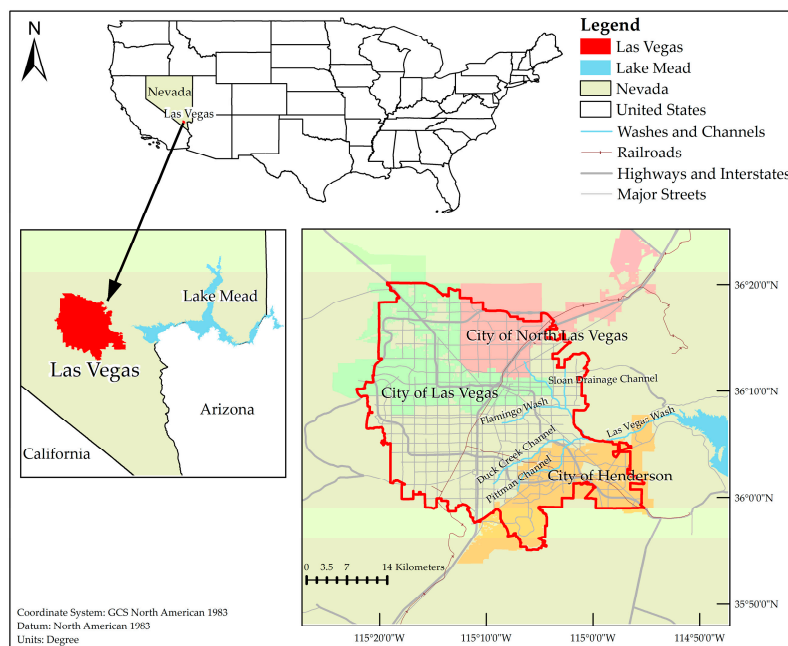
Figure 1. Geographical location of the study area: Las Vegas metropolitan area, Nevada.

3. Data and Methodology

3.1. Data Sources

To create the statistical prediction model, meteorological data for Las Vegas, Nevada, was recorded hourly and was obtained from the National Oceanic and Atmospheric Administration (NOAA)'s National Centers for Environmental Information (NCEI) Center for Weather & Climate (CWC) website. The eleven variables used in this study were precipitation, average temperature, minimum temperature, maximum temperature, dew point depression temperature, diurnal temperature, wind speed, wind direction, percent calm wind, temperature principle component index (assigned as PCA1), and wind and precipitation principle component index (assigned as PCA2). Monthly residential metered water consumption was obtained from the Las Vegas Valley Water District (LVVWD) from 1990

to 2014 (300 months). We only considered the water use for the residential sector of the Las Vegas municipal area. Residential water consumption is significantly reflective of the resident population. Thus, we normalized the water consumption by the resident population to remove the influence of the population factor. The resident population information was also obtained from the LVVWD.

The weather data was retrieved from only one weather station with a reliable continuous record, located at the McCarran International airport. The monthly weather variables were averaged from hourly data. For the maximum and minimum temperature, the value was sorted to compute an absolute daily maximum and minimum temperature. Dew point depression was also calculated from the temperature minus dew point temperature, and the diurnal temperature was calculated from the difference between the maximum and minimum temperature on each day. For the monthly percent calm wind, the percentage of calm wind was calculated from the percentage frequency that was reported as zero wind speed within a month. Principle component 1 (PCA1) and principle component 2 (PCA2) were results from the first two components using principle component analysis to combine weather factors that are highly collinear into a single component. We chose the two most explained components, which give two climate index time-series. One represents mainly the temperature component index (PCA1), and the other represents mainly the precipitation and the wind related component index (PCA2).

3.2. Data Analysis and Data Transformation

3.2.1. Trend Analysis

The residential water consumption per capita from 1990 to 2012 in Las Vegas demonstrates a decreasing trend, as shown in Figure 2. This decrease accounted for 39% of the area's water consumption per capita in 1990. Figure 2 shows the comparison of plots between municipal water consumption in Las Vegas resulting from the SNWA's water consumption projection, the SNWA's conservation achievement, and the average annual residential water consumption in Las Vegas during 1990–2012.
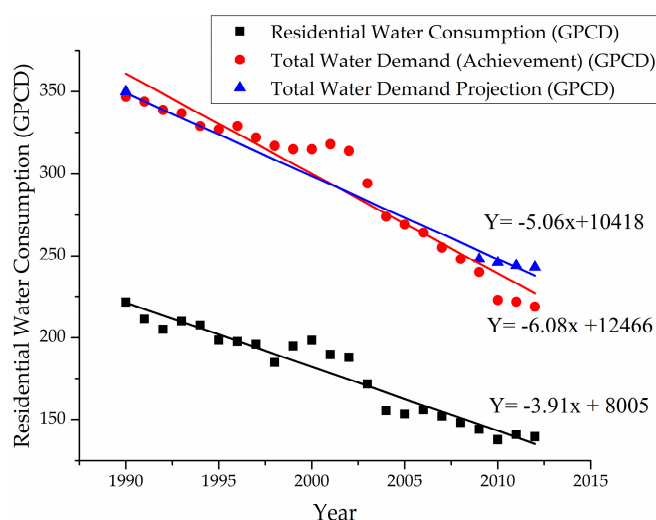
Figure 2. Comparison of the Southern Nevada Water Authority (SNWA)'s water consumption projection (gallon per capita per day, (GPCD)), the SNWA's water conservation achievement [1] (GPCD), and the average annual residential water demand (GPCD) in Las Vegas during 1990–2012. [1] (Data compiled from SNWA, 2014).

SNWA achieved their goal of following the conservation plan (Figure 3) to reduce water demand from 350 gallons per capita per day (GPCD; 1323 L per capita per day (LPCD)) in 1990 to 243 GPCD (918.5 LPCD) in 2012. The actual water demand in 2012 was 219 GPCD (827.8 LPCD), which exceeded their projections. SNWA claimed that the water conservation achievement consistently exceeded

their reduction goals as a result of all adopted conservation programs [3]. The overall SNWA water conservation achievement for the Las Vegas Valley's residents and businesses during 1990 to 2012 resulted in a decrease of water demand per capita per day by 6.08 GPCD (22.98 LPCD) each year (Figure 2). For the residential sector, the decreasing trend in water consumption in Las Vegas was aligned with the decrease achieved by SNWA, with an average linear decreasing rate of 3.91 GPCD/year (14.78 LPCD/year).
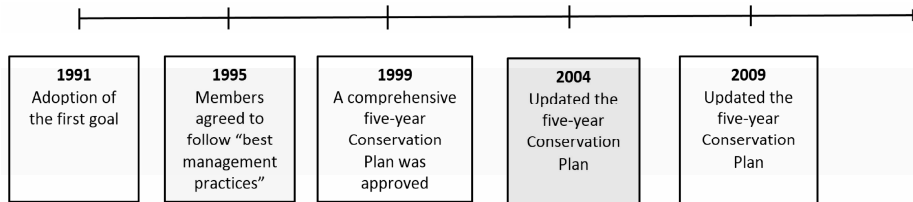

Figure 3. Timeline of conservation adoption goal and comprehensive plan for Las Vegas.

The result of the Pearson correlation coefficient between the SNWA's water conservation achievement and the residential water demand was 0.98, which showed the strength of the correlation between the SNWA's conservation achievement as a result of the conservation programs and the residential water consumption in Las Vegas.

3.2.2. Data Transformation

The time-series analysis assumes that the amount of variability in a time-series is constant across time. To stabilize the variance, we applied a natural log transformation to each variable (both water demand and climate factors) before the next step (trend and seasonality removal process). Figure 4 shows the original data of monthly water consumption and a meteorological factor (dew point depression) that have inconstant variance over time compared to the natural log-transformed data of monthly water consumption and the meteorological factor.
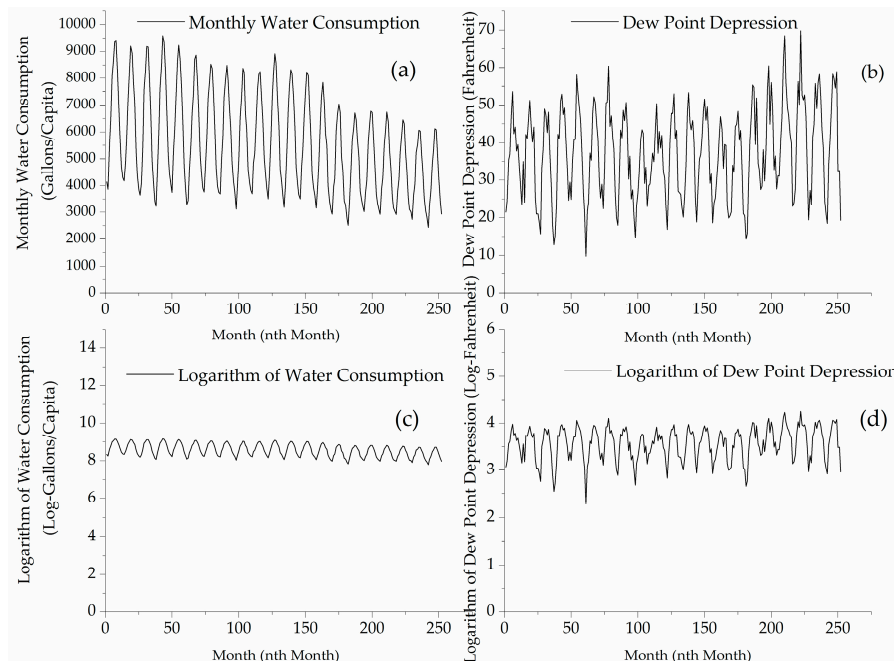

Figure 4. Plots of monthly time-series data and log-transformed time-series data for Las Vegas during 1990–2010: (**a**) monthly water consumption; (**b**) monthly average daily dew point depression; (**c**) natural log-transformed monthly water consumption; (**d**) natural log-transformed dew point depression.

3.3. Methodology

3.3.1. Time-Series Analysis: Model Description and Assumptions

A time-series analysis aims to identify and forecast the future patterns in a sequence of numbers over time (time-series data are correlated among themselves). For more than one variable, multivariate time-series analysis, such as ARIMAX, can be used to model the relationships among component series as well as to forecast those components [25].

As water consumption behavior and climate factors are, in fact, very complex systems, which involve trend and seasonality variations, a simple regression model cannot be applied. The process of time-series analysis is used to analyze water consumption series and to model the time-series, which accommodates trend, seasonality, and autocorrelation where the data that is close to each other tends to be more correlated than data that is chronologically far apart.

We assume that the region's water conservation policy, economics, and climate have impacted its historical water demand. The inclusion of historical water demand in our time-series model as an independent variable (in autoregressive terms) can indirectly represent those influences. In addition, normalizing the demand data by the population numbers can account for the effect of the increasing population. By adding a climate factor as an input into the predictive model, and using long-term climate data, we hypothesize that the climate factor will explain an underlying pattern due to climate change. Due to multicollinearity among the climate variables, and simplification of the empirical model, we preferred to add only a single climate factor in the time-series model, and conducted principle component analysis to combine all related climatic factors into one index.

3.3.2. Differencing for Removing Trend and Seasonality

Seasonality is one of the characteristics of time-series data. For the monthly water consumption data, seasonality patterns show as a 12-month cycle. For time-series analysis, trend (low frequency content) and seasonality (cycles) in the data should be removed to analyze the underlying pattern in the residuals. Thus, we conducted the 12-month differencing process to remove trend and seasonality from the logarithm of the time-series before starting the analysis using the ARIMA and ARIMAX time-series processes. Figure 5 represents the water consumption time-series after removing trend and seasonality effects.
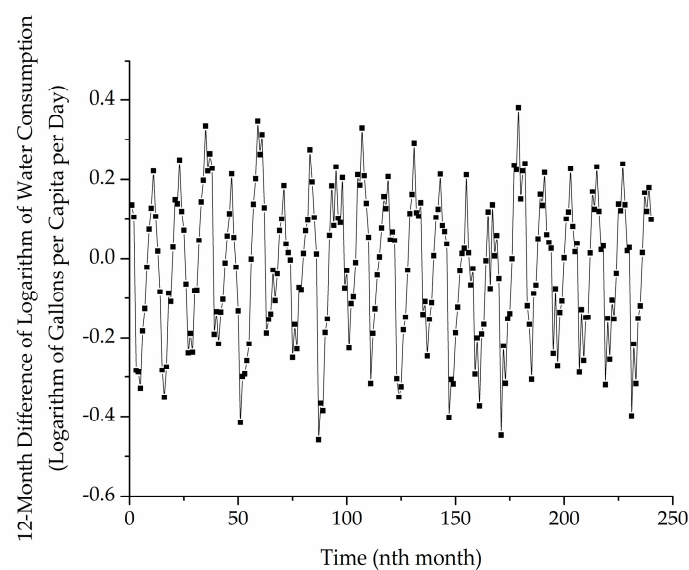
Figure 5. The 12th difference of the natural logarithm of water consumption in Las Vegas from 1990 to 2010.

3.3.3. Model Development: Transfer Function-Noise Model (ARIMAX)

Besides the dynamic behavior of water consumption, it is usually the case that meteorological factors changing from one level to another may have no immediate effect on the water consumption due to the inertial effect of climate to water consumption. Instead, this may produce delayed responses for the water consumption results. Moreover, in a system of water demand, other non-climate factors besides population and policy may affect water consumption. By accounting for the cross lags of the climatic variables as an independent variable and attributing the non-climate effect on water consumption as disturbance, or white noise, the ARIMAX model can capture both a deterministic dynamic system and a stochastic disturbance [26].

Some researchers have used the transfer function model to forecast water consumption time-series [20,27]. A transfer function model is a model that is composed of one output series and two or more input time-series, which are correlated to each other [26].

In the transfer function model, we assume that two time-series, after natural log transformation and differencing processes, denoted as $Z(t)$ and $H(t)$, respectively, are both stationary, meaning that the series has constant means, and the covariance of variables is not dependent on time. Transfer function models are designed to exploit, for predictive purposes, the relationship between two time-series when one acts as a leading indicator for the other [28].

The transfer function with noise model (ARIMAX) can be written as follows

$$Z(t) = C + v(B)H(t) + N(t) \tag{1}$$

where $Z(t)$ is the output series (dependent variable), $H(t)$ is the input series (independent variable), C is a constant term, and $v(B)$ is the transfer function weights for the input series $H(t)$, which is modeled as a ratio of numerator polynomials and denominator polynomials, and can be written as

$$v(B) = \frac{\omega_m(B)}{\delta_r(B)} = \frac{(\omega_0 - \omega_1 B - \omega_2 B^2 - ... - \omega_m B^m)}{(1 - \delta_1 B - \delta_2 B^2 - ... - \delta_r B^r)} \tag{2}$$

where $\omega_m(B)$ is the numerator operator of order m of the transfer function, $\delta_r(B)$ is the denominator operator of order r of the transfer function, and $N(t)$ is the stochastic disturbance of the system that is independent of the input series, and can be written as

$$N(t) = \frac{\theta_q(B)}{\phi_p(B)} a_t = \frac{(1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q)}{(1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p)} a_t \tag{3}$$

where $\theta_q(B)$ is the moving average operator of order q, $\phi_p(B)$ is the autoregressive operator of order p, and a_t is white noise with 0 mean and constant variance.

The time-series analysis was conducted for water consumption with eleven separate variables: maximum temperature, minimum temperature, average temperature, dew point depression, diurnal temperature, precipitation, wind speed, wind direction, percent calm wind, PCA1 index, and PCA2 index. These variables will be examined as an input series in this analysis.

The logarithm of water consumption and the logarithm of the climate variable were 12-month differenced before fitting the transfer function model. Thus, the time-series ARIMAX model can be written in the following forms

$$(1 - B^{12})(Y_t) = C + \frac{\omega_r(B)}{\delta_m(B)}(1 - B^{12})(X_{t-b}) + \frac{\theta_q(B)}{\phi_p(B)} a_t \tag{4}$$

where Y_t is the logarithm of water consumption; X_{t-b} is the logarithm of climate factor with the lead lag b month; and $(1 - B^{12})$ is the 12-months difference operator; and a_t is the forecasting error $(y_t - \hat{y}_t)$, which has a white noise characteristic. Please note that the back shift operators (B) are defined as $B^k Y_t = Y_{t-k}$.

For regression assumptions in the transfer function process, we pre-whitened to obtain stationary data before doing the transfer function process. We then used a Q-Q plot test, a residual autocorrelation function (ACF) plot, and a partial autocorrelation function (PACF) plot to check for normality and the independent and identically distributed (IID) property of the residual after the transfer function process.

Thus, in this analysis, the historic series of monthly residential water consumption in Las Vegas during 1990–2009 were modeled using ARIMAX models and the differencing method for removing trend and seasonality. The monthly water consumption data from 2010 through 2014 were used for prediction performance evaluation. The model and forecast results of the water consumption series are shown in following section.

3.3.4. Model Selection

To determine which meteorological factor explains the most variance in water consumption, the comparison for each of the time-series fitted model was conducted. To compare each of the models between time-series, in which the models are not nested to each other, Akaike's information criterion (AIC) is the most commonly used criterion for determining the best model. Finding the best exogenous variable incorporated in the ARIMAX model determines the model that shows the lowest AIC value, which indicates a parsimonious model.

$$AIC = -2\log(L) + 2(p+1) \tag{5}$$

where L is the likelihood, and p is the number of unknown elements. Thus, the better the model is, the lower the resulting AIC number.

For forecasting performance measures, the performance of eleven models was assessed by Coefficient of Determination (R^2), Mean Absolute Percentage Error (MAPE), Relative Root Mean Square Error (RRMSE), and Average Relative Error (ARE), where:

$$R^2 = 1 - \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{6}$$

$$MAPE = \frac{\frac{1}{n}\sum_{i=1}^{i=n}|y_i - \hat{y}_i|}{\overline{y}} \times 100 \tag{7}$$

$$RRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{i=n}(y_i - \hat{y}_i)^2}}{\overline{y}} \times 100 \tag{8}$$

$$ARE = \frac{1}{n}\sum_{i=1}^{i=n}\frac{|y_i - \hat{y}_i|}{y_i} \times 100 \tag{9}$$

where y_i is the observed data, $\overline{y}$ is the average of the observed data, and $\hat{y}_i$ is the forecasted data.

4. Results

4.1. Model Development Results

The correlation coefficient reported in Table 1 is the Pearson correlation coefficient between the 12-month differences of the logarithm of the monthly water consumption, as shown in Figure 5, and the 12-month differences of the logarithm of the monthly meteorological variables. The result shows that the 12-month differences of the logarithm of the monthly dew point depression highly correlated with

the 12-month differences of the logarithm of the monthly water consumption. Thus, after the trend and seasonality are removed by 12-month differencing, the residual pattern in dew point depression has a significant positive correlation of the underlying pattern of the water demand, with r = 0.734, while precipitation gives a significant negative correlation, with r = 0.550 (Table 1).

Table 1. The Pearson correlation coefficient results between the 12-month difference of the logarithm of water consumption and meteorological parameters input series in Las Vegas during 1990–2009 [a].

| Meteorological Parameter	Pearson Correlation (r)
Maximum Temperature	0.369 **
Minimum Temperature	−0.024
Average Temperature	0.397 **
Dew Point Depression	0.734 **
Diurnal Temperature	0.638 **
Precipitation	−0.550 **
Wind Speed	−0.031
Wind Direction	0.054
Percent of Calm Wind	0.059

[a] The results are produced from statistical package SPSS version 23, ** Correlation is significant at the 0.01 level (two-tailed).

Table 2 shows the comparison of the Akaike's information criterion (AIC) results of the proposed ARIMAX models for each meteorological variable and the R-Squared results. The results show that the log transformation of the monthly dew point depression gives the lowest AIC number and the highest R-Squared value when it is regressed on the log transformation of the monthly water consumption. The lowest AIC means a model can explain more of the variance than another comparative model by taking into account overfitting. The results indicate that historical series of log-transformed dew point depression can help explain the variation of the log-transformed water consumption series from 1990 to 2009 for R-Squared = 98.88%, which is the best fitting model among all meteorological candidates (Table 2). The plot of the model-fitted water demand value using ARIMAX with dew point depression versus actual water demand value is shown in Figure 6. Thus, dew point depression is the main factor, accounting for the most variation in water consumption in Las Vegas during 1990–2009.

Table 2. Akaike's information criterion (AIC) results and R-Squared of model fittings with meteorological parameters input series for the logarithm of water consumption in Las Vegas during 1990–2009 [a].

Parameter	AIC	R-Squared (%)
ARIMAX with log dew point depression	−856.58	98.88
ARIMAX with log average temperature	−824.76	98.72
ARIMAX with log diurnal temperature	−818.45	98.67
ARIMAX with PCA1 *,[b]	−818.13	98.68
ARIMAX with log precipitation	−799.63	98.55
ARIMAX with PCA2 **,[b]	−785.64	98.46
ARIMAX with log maximum temperature	−785.30	98.48
ARIMAX with log minimum temperature	−775.06	98.40
ARIMAX with log wind speed	−773.63	98.47
ARIMA (No climate factor)	−769.60	98.34
ARIMAX with log wind direction	−765.16	98.44
ARIMAX with log percent of calm wind	−713.95	98.44

[a] The results were produced from statistical package SAS version 9.3. [b] PCA1 and PCA2 were calculated from SPSS version 23 using principal component extraction with varimax rotation method. * PCA1 is the component index that represents of maximum temperature (Fahrenheit), minimum temperature (Fahrenheit), average temperature (Fahrenheit), dew point depression (Fahrenheit), and diurnal temperature (Fahrenheit). ** PCA2 is the component index that represents of wind direction (degree), percent calm wind (percent), wind speed (mile/hour), and precipitation (inches).
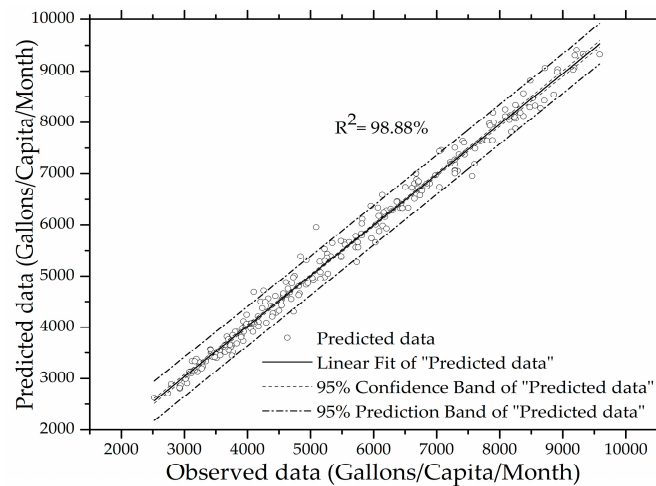
Figure 6. Water consumption plot between observed and predicted data with 95 percent confidence interval using ARIMAX with dew point depression model.

After trial and error with autoregressive and moving average parameters, the final model result for the individual meteorological factors using Equation (4) yielded the lowest AIC value (Table 2). The parameter estimates for each ARIMAX model are shown in Table 3.

Table 3. Parameter estimates of the model fittings and standard errors (in parentheses) results for the transfer function-noise model (ARIMAX) during 1990–2009.

Input	b	μ	ω_0	δ_1	δ_9	ϕ_1	ϕ_2	ϕ_{12}	θ_2	θ_{10}	θ_{24}
No Input (ARIMA)		−0.021				0.755		−0.727			0.606
		(0.003)				(0.044)		(0.059)			(0.070)
Dew Point Depression		−0.022	0.124			0.744		−0.663		−0.115	0.481
		(0.004)	(0.012)			(0.046)		(0.063)		(0.060)	(0.075)
Average Temperature		−0.022	0.346			0.854		−0.731	0.231		0.484
		(0.003)	(0.042)			(0.039)		(0.058)	(0.063)		(0.074)
Diurnal Teperature		−0.020	0.182			0.740		−0.681			0.538
		(0.003)	(0.024)			(0.046)		(0.061)			(0.073)
Maximum Temperature		−0.021	0.211			0.757		−0.729			0.585
		(0.003)	(0.050)			(0.044)		(0.058)			(0.072)
Minimum Temperature		−0.022	0.040			0.813		−0.707	0.163		0.586
		(0.003)	(0.018)			(0.043)		(0.059)	(0.060)		(0.069)
PCA1		−0.022	0.064			0.827	−0.197	−0.694			0.496
		(0.004)	(0.008)			(0.042)	(0.072)	(0.061)			(0.076)
PCA2		−0.019	−0.018			0.748		−0.692			0.601
		(0.003)	(0.004)			(0.045)		(0.060)			(0.070)
Percent Calm Wind	6	−0.022	0.013	0.490	−0.543	0.746		−0.654			0.404
		(0.005)	(0.006)	(0.055)	(0.062)	(0.047)		(0.065)			(0.080)
Precipitation		−0.021	−0.017			0.754		−0.715			0.609
		(0.003)	(0.004)			(0.044)		(0.059)			(0.070)
Wind Direction	4	−0.023	−0.104			0.772		−0.736			0.544
		(0.004)	(0.048)			(0.043)		(0.060)			(0.075)
Wind Speed	3	−0.022	0.058			0.773		−0.734			0.539
		(0.004)	(0.023)			(0.043)		(0.059)			(0.075)

Notes: b represents the month lag number for meteorological input (pure time delay for the input series effect). μ represents mean term. ω_0 represents overall regression factor. δ_1 and δ_9 represent the denominator factor for an input series at lag 1 and 9, respectively. ϕ_1, ϕ_2, and ϕ_{12} represent the autoregressive factor at lag 1, 2, and 12, respectively. θ_2, θ_{10} and θ_{24} represent the moving average factor at lag 2, 10, and 24, respectively. All parameters were calculated by the conditional least-square method (CLS) at the significant level ($\alpha = 0.05$).

For the ARIMAX model with the independent variable of the logarithm of dew point depression, the analysis of the transfer function-noise model derived from Equation (4) with the autoregressive and moving average lag results from Table 3 suggest the identification displayed in Equation (10).

$$(1 - B^{12}) \log{(water)}_t = \mu + \omega_0 (1 - B^{12}) \log{(dewpointdepression)}_t + \frac{(1 - \theta_{10}B^{10} - \theta_{24}B^{24})}{(1 - \phi_1 B)(1 - \phi_{12}B^{12})} a_t \quad (10)$$

Replacing the parameter estimates from Table 3 in Equation (10), the deterministic equation for the ARIMAX model of the logarithm of dew point depression can be determined and be used for forecasting.

4.2. Forecasting Results

Using deterministic equations derived from Equation (4) and the parameter estimates in Table 3, we can forecast water demand by using actual meteorological factors. To see how climate factors can impact the future water demand, and to validate the fitted ARIMAX model during 1990–2009, we forecasted the water demand 12, 24, 36, 48, and 60 months out with known climate factors and compared it with the ARIMA (no climate input) model. We use R-Squared, MAPE, RRMSE, and ARE for the forecast testing measures during 2010, and use MAPE for the forecasting measure during 2010–2014. Table 4 compares the predicted monthly water consumption between the univariate time-series method (ARIMA) and the transfer function-noise method (ARIMAX) with a climate factor for the Las Vegas metropolitan area in 2010. The maximum temperature gives the highest R-Squared value for the water demand forecasting (99.33%). The forecasting measures of MAPE, RRMSE, and ARE for the ARIMA (no climate input), with the ARIMAX of maximum temperature input displayed in parentheses, were 3.80% (1.97%), 4.60% (2.38%), and 4.09% (2.05%), respectively. This ARIMAX model of maximum temperature performance on the monthly water consumption prediction is superior to the ARIMA (no input climate) model and the transfer function-noise model of other climate variables during 2010. The comparison between the ARIMA model and the ARIMAX model of maximum temperature highlights that the average 12-month prediction performance of the ARIMAX model improved by 50% based on MAPE, RRMSE, and ARE (Table 4). The absolute difference of water consumption between observed and forecast values were calculated from the ARIMA (no climate input) model and the ARIMAX of maximum temperature model as 1918 and 994 gallons per capita (7261 and 3764 liters per capita), respectively. Figure 7 illustrates the discrepancy between the predicted water consumption from the ARIMAX model's top four factors from Table 4 and the ARIMA (no climate input) model and the observed water consumption.

Table 4. R-Squared, Mean Absolute Percentage Error (MAPE), Relative Root Mean Square Error (RRMSE), Average Relative Error (ARE), and Percent improvement from ARIMA (in parentheses) of forecasting with meteorological parameters input series for the logarithm of water consumption (GPCD) in Las Vegas 2010.

Parameter	R-Squared (%)	MAPE (%)	RRMSE (%)	ARE (%)
ARIMAX with log maximum temperature	99.33	1.97 (48.2)	2.38 (58.4)	2.05 (53.7)
ARIMAX with log dew point depression	99.12	2.10 (44.7)	2.75 (48.7)	2.14 (51.3)
ARIMAX with PCA1	98.95	2.49 (34.5)	3.00 (42.1)	2.95 (30.0)
ARIMAX with log average temperature	98.35	3.10 (18.4)	3.75 (22.4)	3.68 (10.8)
ARIMAX with log wind speed	98.05	3.48 (8.4)	4.08 (13.7)	3.85 (6.3)
ARIMAX with log wind direction	97.80	3.77 (0.8)	4.33 (7.1)	3.87 (5.8)
ARIMAX with log percent of calm wind	97.59	3.56 (6.3)	4.53 (1.8)	3.95 (3.7)
ARIMA (no climate factor)	97.52	3.80	4.60	4.09
ARIMAX with log minimum temperature	97.51	4.00	4.60	4.44
ARIMA with log diurnal temperature	95.09	5.65	6.47	5.97
ARIMAX with log PCA2	93.77	6.22	7.28	6.13
ARIMAX with log precipitation	74.12	11.28	14.85	9.85
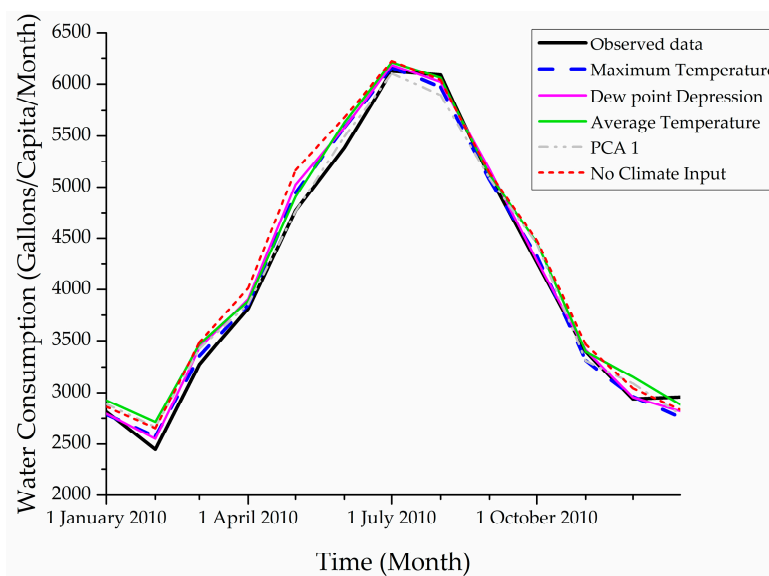
Figure 7. Time-series of observed monthly water consumption and predicted data calculated from the ARIMA (no climate input) model, and the ARIMAX with maximum temperature, average temperature, dew point temperature, and PCA1 models in 2010.

The long-term performance of the ARIMA and ARIMAX models of the singular input series models were evaluated by computing MAPE statistics for forecasts from 12 months to 60 months ahead. Table 5 gives the forecasts' results for the period from January 2010 to December 2014. From Table 5, the ARIMA model with no meteorological input gives the average 12-month MAPE for the 1st, 2nd, 3rd, 4th, and 5th year forecast at 3.80%, 2.85%, 2.87%, 3.08%, and 3.93%, respectively. The ARIMAX model of dew point depression and average temperature, displayed in parentheses, gives a lower MAPE forecast compared to the ARIMA model (except the 3rd year for dew point depression) at 2.10% (3.10%), 2.49% (2.27%), 2.96% (2.66%), 3.02% (3.03%), and 3.21% (2.95%), respectively (Table 5). Dew point depression and average temperature show a forecast improvement from the ARIMA no-climate model at about 15%. Of the five-year average MAPE, the ARIMAX model of dew point depression gives the lowest average MAPE, at 2.76%, and the ARIMAX model of the average temperature gives the second lowest average MAPE, at 2.80%. Moreover, the best forecasting climate factor for the 1st, 2nd, 3rd, 4th, and 5th year forecast is maximum temperature (1.97%), average temperature (2.27%), PCA2 (2.48%), minimum temperature (2.66%), and average temperature (2.95%), respectively. These results suggest that water demand is a dynamic system that can be most influenced by different climate factors at different time periods. Thus, the climate factor can describe water demand best on average over long periods, especially under future uncertainty; this factor gives the most significant impact on the water demand system. The time-series plot of the forecasting results from the ARIMAX model of the logarithmic dew point depression during 1990-2014, along with the actual data, are displayed in Figure 8.

Table 5. Lists of meteorological factors in ARIMAX model and their MAPE (%) forecasting error measure with respect to the forecasting periods with descriptive statistics.

Input [1]	Forecasting Period (n[th] Month) [2]	Mean (%)	Standard Deviation (%)	Minimum (%)	Maximum (%)
No Input (ARIMA)	1–12	3.80	2.70	0.70	9.40
	13–24	2.85	1.59	0.31	4.62
	25–36	2.87	1.88	0.44	6.35
	37–48	3.08	1.97	0.69	7.02
	49–60	3.93	2.05	0.22	6.62

Table 5. *Cont.*

Input [1]	Forecasting Period (n_{th} Month) [2]	Mean (%)	Standard Deviation (%)	Minimum (%)	Maximum (%)
Dew Point Depression	1–12	2.10	1.85	0.29	6.03
	13–24	2.49	1.75	0.56	5.93
	25–36	2.96	1.82	0.57	6.01
	37–48	3.02	1.67	0.57	6.48
	49–60	3.21	1.84	0.48	5.57
Average Temperature	1–12	3.10	2.20	0.02	6.37
	13–24	2.27	1.41	0.10	5.00
	25–36	2.55	1.66	0.00	4.96
	37–48	3.03	1.46	0.89	5.61
	49–60	2.95	1.41	0.26	4.63
Diurnal Temperature	1–12	5.65	3.28	1.78	12.65
	13–24	3.47	2.96	0.58	8.75
	25–36	2.60	1.54	0.67	5.27
	37–48	2.87	2.66	0.25	8.81
	49–60	3.39	2.56	0.69	9.13
Maximum Temperature	1–12	1.97	1.40	0.52	4.69
	13–24	3.67	2.40	0.66	6.98
	25–36	4.37	2.29	1.02	7.99
	37–48	4.64	1.67	1.49	7.53
	49–60	4.75	2.41	0.51	7.82
Minimum Temperature	1–12	4.00	2.37	0.42	7.81
	13–24	2.73	1.54	1.01	5.40
	25–36	2.64	1.56	0.50	5.48
	37–48	2.66	2.44	0.30	8.21
	49–60	3.51	2.09	0.28	6.71
PCA1	1–12	2.49	1.73	0.18	5.19
	13–24	3.38	2.39	0.02	7.22
	25–36	4.52	2.74	0.08	8.20
	37–48	4.70	1.93	1.16	7.74
	49–60	5.84	2.14	2.55	8.91
PCA2	1–12	6.22	3.95	0.24	15.6
	13–24	3.63	2.91	0.32	9.63
	25–36	2.48	1.64	0.17	4.94
	37–48	3.18	2.77	0.13	9.42
	49–60	4.38	3.13	0.01	10.11
Percent Calm Wind	1–12	3.56	2.92	0.14	8.78
	13–24	3.26	1.87	1.18	5.89
	25–36	3.57	2.56	0.02	7.71
	37–48	4.04	2.18	0.07	6.89
	49–60	4.87	2.29	0.11	8.02
Precipitation	1–12	11.28	10.08	1.35	25.91
	13–24	5.59	6.57	0.35	22.71
	25–36	5.23	4.43	0.33	14.98
	37–48	6.50	5.80	0.08	16.75
	49–60	7.47	5.22	0.96	16.25
Wind Direction	1–12	3.77	2.22	0.13	6.66
	13–24	4.00	2.11	0.60	6.78
	25–36	5.09	2.24	1.32	7.71
	37–48	5.09	1.57	2.49	6.91
	49–60	5.72	2.78	0.16	9.29
Wind Speed	1–12	3.48	2.22	0.28	6.59
	13–24	2.94	1.51	0.08	4.73
	25–36	3.26	1.87	0.38	6.13
	37–48	3.80	1.67	1.11	7.24
	49–60	4.53	1.90	1.99	7.12

Notes: [1] Actual meteorological data input is used for the forecasting. [2] The forecast period is time period during 2010–2014.
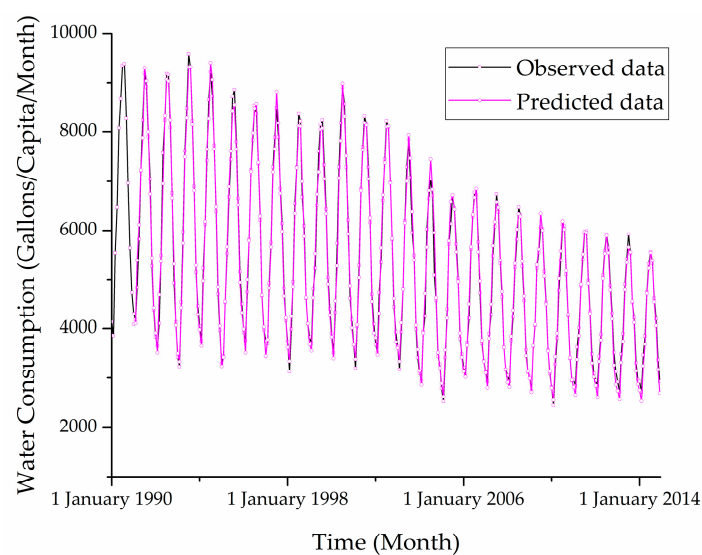
Figure 8. Time-series of monthly water consumption observed and predicted data from 1990 to 2014.

4.3. Sensitivity Analysis Results

To assess the potential impacts of climate change and improve an understanding of the interactions between climate and water demand, sensitivity tests on water consumption due to climate change were conducted (Table 6). By using the two best performances for long-term forecasting of water demand using the ARIMAX models, the results showed a 1% increase or decrease of dew point depression, resulting in a change of water demand by 0.12%, respectively. For average temperature, a 1% increase or decrease will result in a change of water demand by 0.35%, respectively. For every 10% increase or decrease of the climate factors, it will result in an approximately one order of magnitude of 1% change for water demand, respectively. These results suggest that the water demand in Las Vegas is more susceptible to changes in average temperature than changes in dew point depression.

Table 6. Sensitivity analysis of change in monthly per capita water demand as a result of percent change of climates using the ARIMAX models.

Climatic Scenarios	Dew point Depression [1] (Fahrenheit)	Demand Change	Predicted Water Demand [1] (GPC) [2]	Average Temperature [1] (Fahrenheit)	Demand Change	Predicted Water Demand [1] (GPC) [2]
Base value	21.1	Base value	2797.5	48.7	Base value	2925.1
1% increase	21.3	0.12% increase	2800.9	49.2	0.35% increase	2935.2
1% decrease	20.9	0.12% decrease	2794.0	48.2	0.35% decrease	2915.0
10% increase	23.2	1.19% increase	2830.7	53.6	3.35% increase	3023.2
10% decrease	19.0	1.30% decrease	2761.2	43.8	3.58% decrease	2820.3

Note: [1] The data period used in the analysis is from January 2010; [2] GPC = Gallons Per Capita.

5. Discussion

In this study, all climate time-series values were obtained from one reliable weather station (McCarran International Airport) that has continuously collected the data since 1949. We assume that these climate data represent the changing climate patterns in the Las Vegas metropolitan area. However, when using one weather station for the meteorological factors, the weather data may not account for spatial variations (latitude-longitude effect), and this could impact the accuracy of the findings. To be more precise, for the climate impact investigation, one could use climatic data from several stations, interpolate climate factors spatially, and use water demand data at the respective station neighborhoods for water demand modeling.

A log transformation of the data for both water consumption and the climate factor time-series provides those time-series with more uniform variability. The log transformation is suitable for non-negative variables and time-series data that has exponentially increasing/decreasing trends. Moreover, because the scales of the model's variables significantly differ in magnitude, it necessitates the use of the log-log time-series regression model, which gives more stationary than absolute differences. The multicollinearity analysis of meteorological factors is conducted through principle component analysis. An investigation found that climatic variables, including maximum temperature, minimum temperature, average temperature, diurnal temperature, and dew point depression, influenced one another, which can be grouped as PCA1. Also, wind speed, wind direction, precipitation, and percent calm wind can be clustered together according to the principle component analysis to give another input, the PCA2 time-series, to test through the ARIMAX water consumption model.

Because per capita water use in Las Vegas was found to be decreasing, this declining trend was a result of the conservation program that was implemented in the 1990s in response to population growth and the impacts of a slow economy [2]. Thus, the trending patterns in water consumption may be due to regulatory and economic factors. However, the variation of water consumption can be explained by the weather factor [4,6,11,12,27]. Thus, in the time-series with the climate input model, the effects of non-meteorological factors, such as conservation policies and socioeconomics, may appear in the historical water demand data (autoregressive terms) as well as in stochastic noise (moving average terms).

After removing underlying trend and seasonality patterns for both the water and the climate time-series, the correlation of the random variation between climate factors and water demand can reveal the impact of climate factors on water demand. Table 1 gives the results of the correlation of random variation between climate factors and water demand. The random variation of water demand and climate factors can be referred to as the rate of yearly change of the logarithm of water consumption and the rate of yearly change of the logarithm of climate factors. The results show that dew point depression gives the highest positive significant correlation of 0.73, while precipitation gives the highest negative significant correlation of -0.55 (Table 1).

The water demand model uses a time-series analysis to show that current water use is strongly influenced by past water use, as well as by current and past climate factors. The time-series model takes into account behavioral responses and time lags between policies and residents' water consumption decisions [29,30]. Based on the interview with the Southern Nevada Water Authority (SNWA), the SNWA closely monitored and controlled residential water consumption per capita following their water conservation plan in 2009. Thus, the water consumption trend and seasonal patterns would ordinarily be closely related to the previous water consumption record, except there were some unpredictable events, such as a storm (which rarely occurs in Las Vegas), which caused the outlier and irregular variation to the data.

The long-term water demand time-series model, in contrast to the short-term demand model, helps to examine water demand projection and to understand the effects of climate change [10–12,29–31]. The monthly water demand model established the long-term relationships between the climate and water consumption variables. The ARIMAX model accounts for the autocorrelation in the water demand time-series by using the previous month and year and the following month and year of water use as an independent variable, and it also accounts for the cross lags of the climate factors as an independent variable [26]. Thus, the ARIMAX model can be applied intuitively to forecast water demand. However, this ARIMA/ARIMAX methodology suggests that an investigator obtain at least 50 time steps (in this case 50 months) of a dataset to create the time-series model [26]. For forecasting water demand, the model requires future meteorological factor values. Thus, a limitation of the proposed model is that we are required to obtain a predicted meteorological factor before forecasting water demand.

Since the impact of the climate factor on water demand is calculated by improving the accuracy performance (MAPE) from the no-climate input time-series model (ARIMA), we used actual climate

inputs in the forecasting model in order to avoid adding a forecasting error from predicting the climate inputs. The evidence of the climate factor improves the forecasting of water demand as shown in Table 2. Most R-Squared results of each ARIMAX model that has a climate factor as an independent variable are greater than the water demand time-series model without a climate factor, ARIMA. The best-fit model is the ARIMAX model of dew point depression, which gives the highest R-Squared value of 98.88 and the lowest AIC of -856.58 as compared with other competitive climate factors in ARIMAX models. High dew point depression (high temperature with low dew point temperature) reflects warm and dry weather. Thus, dew point depression can be an indirect indicator of water loss due to the evapotranspiration process in the Las Vegas region.

The fitting time-series model with the climate factor as an input series also has a considerably high R-Squared value, at about 98% excepting precipitation, and the prediction performance for the next 12 months has a low mean absolute percentage error (MAPE), at about 2–6% (Table 4). Yet, there is a challenge to estimate climate factors accurately under future uncertainty. The forecasting reliability performance test was conducted and the results showed that the ARIMAX model with dew point depression and average temperature as input series gives a low predictive error of monthly water demand at 2.76% and 2.80% on the 5-year average and low average standard deviation at 1.79% and 1.63%, respectively (Table 5). The results show, on the other hand, that the precipitation factor gives the least reliability in the forecasting, at 7.21% with the average standard deviation at 6.42%. The minimum MAPE results in Table 5 give the notation that in a monthly time frame, water demand can be highly influenced by many climate factors, such as average temperature, PCA1, PCA2, wind speed, percent calm wind, and precipitation, that show an MAPE of less than 0.10%. However, to evaluate the impact of climate change on water demand, we consider a climate factor that explains most of the water demand variation during a long-term period. The fitted model and forecasting results demonstrated that dew point depression is the significant climate factor that impacted water demand in Las Vegas from 1990 to 2014.

Because changing climates influence the increases or decreases in water demand, using the best forecasting ARIMAX model can determine the projected changes in water demand in Las Vegas. The sensitivity analysis results in Table 6 demonstrate the susceptibility of changes in water demand due to changes in dew point depression and average temperature. These results show that dew point depression and average temperature have positive impacts on water demand, and water consumption in the Las Vegas area is susceptible to changes of average temperature about three times more than changes of dew point depression. Based on our ARIMAX models' simulations, the results suggest that the water demand in Las Vegas can be more vulnerable to changes in average temperature than changes in dew point depression.

6. Conclusions

This study examined the relationship between monthly weather variables and water consumption in the Las Vegas municipality area. Using data during 1990 to 2009, the results demonstrate that on average over 20 years, dew point depression has a significant impact on water demand according to the fitted results. By investigating future forecasting, we found that the logarithm of monthly dew point depression and the logarithm of monthly average temperature are good predictors of the logarithm of monthly water consumption in the period of 60 months out. It is likely that dew point depression and average temperature will have an effect in the long-term on water demand in the region through the evapotranspiration process. As indicated by the SNWA (2014) report [3], out of the total water consumption in the Las Vegas area, 60% of the water demand is for consumptive use, which mainly accounts for outdoor activities and irrigation. The ARIMAX, or transfer function-noise, model is particularly accurate because it takes into account temporal autocorrelation, which significantly improves the model's prediction and also explains the trend, seasonality, and random error parts in the model. This time-series with a climatic model allows us to project potential changes in seasonal water demand in Las Vegas as a result of climate change. Moreover, the sensitivity results from the ARIMAX

model provide us a better understanding of the relationship between climate factors and water demand. Thus, for future work, it would be interesting to see how the impact of climate factors on water demand is based on seasons. Even though all meteorological candidates give a high R-Squared value for the model fitting results (Table 2), the forecasting performances of the monthly water demand for each meteorological factor are varied and change with time period. As climate change occurs and the area's population continues to grow, the results of this research could be used to better understand the factors that affect municipal water use, especially in a semi-arid region, and to establish the best prediction methods and strategies for mitigating water stress.

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