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Water demand time series forecast by autoregressive distributed lag (ARDL) co-integration model

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Abstract: This article examines the short- and long-run effects of water price, system input, income, temperature on domestic water demand for Amman area over the period of 1980–2012. An empirical, dynamic autoregressive distributed lag (ARDL) model for water demand is developed on a yearly basis. This approach is capable of testing and analysing the dynamic relationship with time series data using a single equation regressions. Results show the ability of the model to predicting future trends (short- and long-run association). The main results indicate that water demand in limited water environment is partially captured in the long-run by the amount of water reaching the customer. The short- and long-run elasticities of water price (–0.061, –0.028) and high temperature (0.023, 0.054) indicate inelastic behaviour on water demand both in short- and long-run, while the lagged water price has a significant effect on demand. Income represented by gross domestic product (GDP) slightly affects water consumption in the long-run and insignificantly in the short-run (0.24, 0.24). Water consumption is strongly linked to consumption habits measured by lagged billed amount 0.35, and is strongly linked to amount of supplied water both in short- and long-run (0.47, 0.53). These results suggest that water needs should be satisfied first to allow controlling water demand through a good pricing system.

Moreover, the association identified between demand and water system input, and the lesser elasticities of water price and other explanatory variables confirm the condition of water deficit in Amman area and Jordan. The results could be rolled out to similar cities suffering scarce water resources with arid and semi-arid weather conditions.

Keywords: autoregressive distributed lag (ARDL), co-integration, forecast, Jordan, municipal water demand

INTRODUCTION

Water demand description and prediction represent a particular area of interest as scarcity and water need increase resulting in water stress in many regions [Vörösmarty *et al.* 2000]. In this framework, the ability to identify factors affecting the demand and its trend in time is of foremost importance: the multiple factors affecting the trending in water consumption made the guess of the needed water for a given place and time a difficult task. Similarly, the complex interactions between the human society and the natural and anthropic environment make forecasting and predicting a challenging deal [House-Peters, Chang 2011]. The prediction of spatial and temporal patterns of future water use is crucial for the design of water policies, the planning for new sources development and the system expansion. The understanding of the variables underpinning water demand, can also help in designing water allocation policies [Gam *et al.* 2013; Momen, Butler 2006].

Residential water demand has been extensively analysed during the last decades using several formalizations and models to decrypt its relation with the affecting variables [Martínez-Espiñeira 2007]. Models used vary: dynamic or static, time horizon applicability (short, medium or long term), water sources (surface, groundwater or overall water). The researchers that considered the overall water sources have based their work on the assumption that water is a homogenous good, i.e. a good similar in physical composition, and quality but different in price and availability.

This section describes the variables used in developing water demand forecasts. It gives an overview of the previous researches that studied the independent variables behaviour and it main statistical characteristics on water demand. The literature review included selected published research during the past two decades both in world and those in Jordan.

The main explanatory variables (determinants) used in literature to quantify water demand are: the economic aspects (water pricing, income); meteorological and weather factors (temperature, rainfall, drought); demographic characteristics (population and household composition and urban density); and non-price consumption controls applied by the utility, like awareness conservation campaigns [WORTHINGTON, HOFFMANN 2007]. Suitable price variables are the marginal price and the Nordin difference, i.e. the difference between the billed value of the consumed water at marginal price and the total bills [SCHEFTER, DAVID 1985].

Climate change, population growth, the economic development resulting from industrial and agriculture growth create a pressure in water resources to fulfilment of water demands [BERREDJEM, HANI 2017; BOUZNAD *et al.* 2020; MIODUSZEWSKI 2006].

MUSOLESI and NOSVELLI [2007]utilized generalized method of moments (GMM) to develop water demand function and to estimate short-run and long-run price elasticities of panel data of Italian municipalities, also in 2010 the same researchers used the ARDL co-integration approach to shape the water demand equation in the short and long term for Milan. The paper study the factors affecting the water demand, mainly water price and habits. Additionally, climate, income, and productive activity are examined to see their effects on water consumption [MUSOLESI, NOSVELLI 2010].

ARDL co-integration has been also used by Taştan who developed a model to examines the factors affecting water demand consumption in long and short term in Istanbul, Turkey. The paper gave attention to the effect of water price on the water demand. The study included the effects of industrial production, average temperature, total precipitation, and electricity and natural gas prices on water demand [TAŞTAN 2018].

TOUMI and TOUMI [2019] examine the asymmetric causality for renewable energy REC as well as the emissions of carbon dioxide (CE) and real gross domestic product (GDP) in the short and long run using time series data from Kingdom of Saudi Arabia (KSA) between 1990 and 2014, the authors using non-linear autoregressive distributed lag method (NARDL).

HE *et al.* [2019] used environmental tax, GDP, unemployment rate, greenhouse gas emissions, nitrogen oxides emissions, and sulphur oxides emissions to build ARDL model to reports the performance environmental tax levied in 36 countries of OECD from 1999–2014.

Similar to other developing countries, Jordan realized the importance of residential water demand forecasting to cater for economic development and the competition on water between sectors and to plan additional water resources required by economic activities – including agriculture, industry and commercial services besides the population increase and urbanization, which boost the water needs for residential uses.

MWI has tried to estimate future demand; they utilized single coefficient methods, which is based on the population.

Previous researches of water demand gave attention to the effect of household characteristics, together with price variables. Studies on econometric estimation of water demand in Amman used cross-section and panel data over short time periods. Long-run water consumption elasticities have been rarely estimated for Amman.

Water household demand in Jordan has been studied by SALMAN and AL-KARABLIEH [2006] using quarterly aggregate panel data. The model results show the negative effects of the water price on water demand with –0.18 elasticity and positive elasticity for household income 0.02. Moreover, the paper concludes that both water price and household income have inelastic behaviour regarding water demand.

AL-NAJJAR et al. [2011] built two water demand models; the first one was the household water demand, and the second was the per capita water demand. The two models were based on socioeconomic panel data and solved by two-stage least squares (2SLS) method. The results of the paper show that the water price has negative effects on water demand with elasticity of –0.52 and –0.67 for the household demand and per capita water demand respectively, while for the coefficient of household income, a positive income elasticity with a value 0.22 has been obtained. Nevertheless, the paper indicates that the water price and income have insignificant effects on water consumption.

TABIEH *et al.* [2012] use socioeconomic cross-section data focusing on Zarka Basin (which includes Amman) to estimate water demand function. Results indicate that water demand in Zarka Basin is inelastic with respect to the price and income with –0.47 and 0.05 for price and income coefficients, respectively.

ARDL bounds testing approach has been also used to estimate Jordan's residential electricity demand over the period 1980–2013 and to analyse the short and long-run effects of price and income on demand [AJLOUNI 2016].

In this work, municipal water demand determinant dynamics (short- and long-run elasticities) are estimated using the techniques of autoregressive distributed lag (ARDL). The ARDL model for Amman has been specified, estimated and checked using diagnostic analysis developed following the approach developed by PESARAN and SHIN [1999] and PESARAN *et al.* [2001].

The lack of accurate data is an obstacle in modelling residential water use and demand [WORTHINGTON, HOFFMANN 2007]. While most research literature used aggregated data at the utility, basin, water mains, i.e. major pipeline, or community levels, others utilized surveys at the household-level. The aggregated data inherit a concern in matching average water consumption with averages of the related information, coming from different source and representing different time periods. The yearly data can better overcome this concern. The frequency of data used in literature varies from hourly to yearly intervals.

The Authors of this paper believe that using the autoregressive distributed lag (ARDL) co-integration approach in analysing water demand and its affecting factors specifically in water stressed countries may provide a powerful tool to effectively forecast water demand and thus water supply strategies. This research is using ARDL co-integration approach to estimating municipal water consumption elasticities, through estimating long- and short-run elasticities for Amman area. The Author selected to use data with annual frequency for Amman water systems and Jordan due to availability limitation of smaller frequencies.

This work will help providing a dynamic tool to forecast demand for Amman water utilities home for almost half of the population of Jordan that suffers from water scarcity and increasing water stress, financial constraints and other dynamic determinants of water demand.

The developed model will allow the utility and Jordan to in selecting effective water demand management policies and strategies to minimize water supply and demand imbalance based on each policy determinant contribution to demand.

The results could be rolled out to cities similar to Amman in size and conditions suffering scarce water resources and arid and semi-arid weather conditions to develop its policies and strategies.

The main objective of this research is to empirically examine the determinants of water demand for Amman city by estimating and formulating a dynamic a model. The developed model can help Miyahuna (Amman water utility) to develop its water demand management policies and strategies to reduce the gap between the water supply and demand.

The model describes the factors affecting water consumption and helps predicting its short and long run future values in the Amman area. It contributes to the identification of the complex factors and its trend in affecting domestic water consumption which constitute the most important part of the overall water demand. It utilizes an autoregressive distributed lag co-integration model developed using different proposed yearly time series as potential descriptors. The determinants studied include the lagged water consumption (water consumption habit), the per subscriber water consumption, amount of water that input to distribution system, marginal price, the income (gross domestic product) that provides an indication of the development of the lifestyle and the weather conditions represented by the number of days in the year in which temperature exceeds 30°C (average temperature in the study area during peak demand months May–October).

MATERIALS AND METHODS

STUDY AREA

Jordan as well its capital city Amman, started to suffer water deficit since late 1960s that resulted from rapid population growth, increasing number of refugees seeking shelter, expansion of economic activities, and climate change effects, exacerbated by limited financial resources. This put Amman and Jordan water resources under increasing pressure with per capita yearly fresh water share of less than 125 $m^3 \cdot y^{-1}$ [MWI 2013], and obliged Jordan to start shifting available fresh water to municipal uses.

Amman water resources are located far away from the Amman populated area in both horizontal and vertical directions (examples: Zara-Maen water source at 35 km to the west and at an elevation below Amman populated area by 1500 m; Disi wellfield is located at 330 km to the south of Amman and at an elevation lower than Amman by 600 m) (see Fig. 1). This situation adds complication to the cost and management of Amman water systems and utility.

The historical average annual rainfall is less than 200 mm over 92% of the land and 92% of the Kingdom area is desert or

Fig. 1. Jordan location map and location of Amman water resources; source: own elaboration based on GIS background data available about Jordan

rangeland. In 2017, the population is estimated at 9.96 mln living on 89,297 km^2 [Department of Statistics 2020b].

The municipal water uses is steadily increasing while irrigation water is decreasing since more than three decades [MWI 2016]. Figure 2 shows, for the 1994–2014 period, an average increase in municipal water supply of 3.1% while irrigation water decreased by 1.6%. At the Jordan level, the share of municipal water uses increased from 23% to 48% in the 1994–2013 period against 53% for irrigation in 2013.

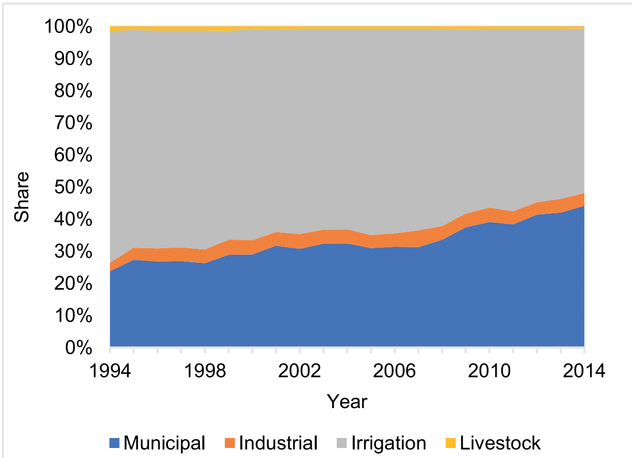

Fig. 2. Percent of water supply share in Jordan; source: own elaboration based on Ministry of Water and Irrigation data [MWI 2013]

Amman is the capital city of Jordan with a population of four million. Residential water use share of Amman municipal water is 86.5% in 2015 (Fig. 3). The remaining is for commercial, governmental and small industrial customers. Most of the uses are indoor.

The Ministry of Water and Irrigation adopted different strategies to face this water stress focusing its interests to supply water to human consumption [MWI 2016].

Modernization of water systems and institutions in Jordan has started late in 1980s. It is only in 1988 that Water Authority of

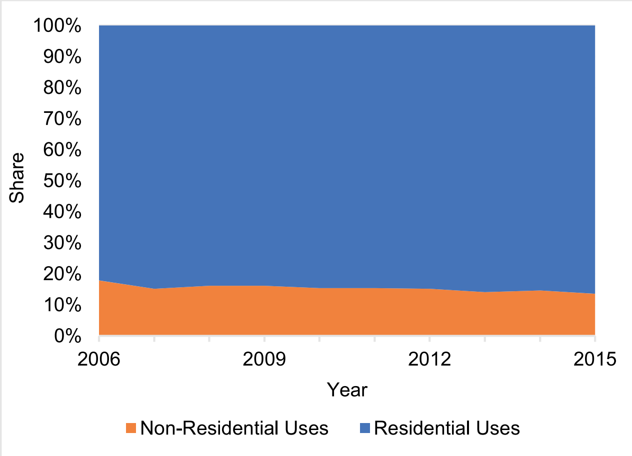

Fig. 3. Amman water uses shares; source: own elaboration based on Miyahuna Billing data

Jordan (WAJ) has been established as a successor of Amman Wastewater Authority with a mandate to provide municipal water and wastewater services. WAJ has assigned the provision of the services within Amman governorate to the Jordan Water Company (Miyahuna) that was established for this purpose in 2007. Later, WAJ and Miyahuna have agreed to widen the service area of Miyahuna to include Madaba Governorate, then Zarqa Governorate and recently Balqa Governorates through management contracts.

WAJ also started to realize the need to invests in exploring new water resources including the implementation of Disi Water Project which started conveying about 100 mln m^3 of fossil water from the southern part of Jordan to Amman area since 2013. The Ministry studied also the possibility of desalinating water from the Red Sea and convey it to Amman area.

The strategies also urged the water utilities including Miyahuna to adopting effective water demand management policies to minimize water supply and demand imbalance, intermittent supply and water preservation measures were also adopted, this create the need to forecast water demand using available historical data including those arranged in the form of time series.

DATA AVAILABILITY

The frequency of the data used is a yearly time series, this enables considering less complex models; HERRERA *et al.* [2010] indicated the need for more complex models that allow for non-linear structure to forecast high frequency demand. WORTHINGTON and HOFFMANN [2007] discussed the same issue in their survey paper. The time series for the available data are presented in Figure 4.

Available data of annual frequency for Amman are collected and screened for irregularities and discrepancies. The yearly data of the selected variables (time series) are used for estimating municipal water consumption elasticities (short- and long-run elasticities for Amman).

The data employed in developing the autoregressive distributed lag (ARDL) model in this research are tabulated in the form of time series (variables/determinants). The source, description and notation of collected time series data are shown in Table 1.

Water demand (use) is estimated at the annual scale throughout the average of water-billed data of one customer and other explanatory variables, as presented in Table 1. The water use – per subscriber billed amount – shows a decreasing trend starting from 1998 until 2000, then it increased (Fig. 4a). The sharp increase in 2011 and the sharp drop in 2012 may be attributed to the shift in the billing cycle and the staggered reading time. In fact, utilities were only billed on monthly basis during 2011, and on quarterly bases elsewhere. Moreover, the average bill value includes the amount paid by the customer for both water and wastewater services as well as a fixed amount.

The water marginal price depicts an increasing trend starting from 1980. The sharp increase in 1982, 1991, 1998, 2011 and 2012 is due to tariff reforms (Fig. 4b).

The supplied amount (system input) has not changed significantly during the 1980s, reaching the peak in 1992, then steadily decreased until 2003 where a small increase is noticed due exploiting the groundwater resources and the increase of Zai water treatment facility capacity (Fig. 4c). An increase was achieved in 2013 and 2014 due to start of operation of the new Disi water resource project.

The population growth rate for Amman shows sharp increases in 1991, 2004 and 2011 due to refugees. These non-normal growth rate affected both the per capita billed amount and the GDP/C.

The declination in per capita gross domestic product at real prices started after 1982 reaching the minimum during the 1989–1991 devaluation of Jordan Dinar. Then started to recover until 2008 peak, with a value of 1237 JD per person. Per capita GDP dropped by a total 17% during 2009–2015 with annual shrinkage rate of 2.85%. The inverse trend direction after 2008 refers to the effect of the financial crisis (Fig. 4d).

The temperature related criterion is number of days in the year in which temperature exceeded the average high temperature during the peak demand months of May–October in Amman (30° C); Marka Airport station in Amman is selected to represent the study area. The temperature time series shows an increasing trend with random oscillation (Fig. 4e). The increasing trend (although the short time-series) may possibly be attributed to climate warming, as the downscaled climatic models show an increasing pattern in temperature.

The general descriptive statistics of all individual variable are calculated using Eviews Software and the results are included in Table 2 while the trend and values are shown in Figure 4. The plots and tabulated data, as well as the process knowledge are fundamental in determining the form of the model to be fit to the data.

CHOICE OF THE VARIABLES

The optimal selection of variables able to adequately capture the demand (i.e., the billed amount) dynamics is discussed here. It includes a judgment of the effect on the dependent variable (*DV*) of the timing selected for the independent variables (*IV*). The chosen variables in this study have been explored internationally, and some of them locally, they show the central role in water demand forecasting [ARBUÉS *et al.* 2003; TABIEH *et al.* 2012].

The explored variables in this study may have a long-run and short-run effect on the dependent variable, as discussed on

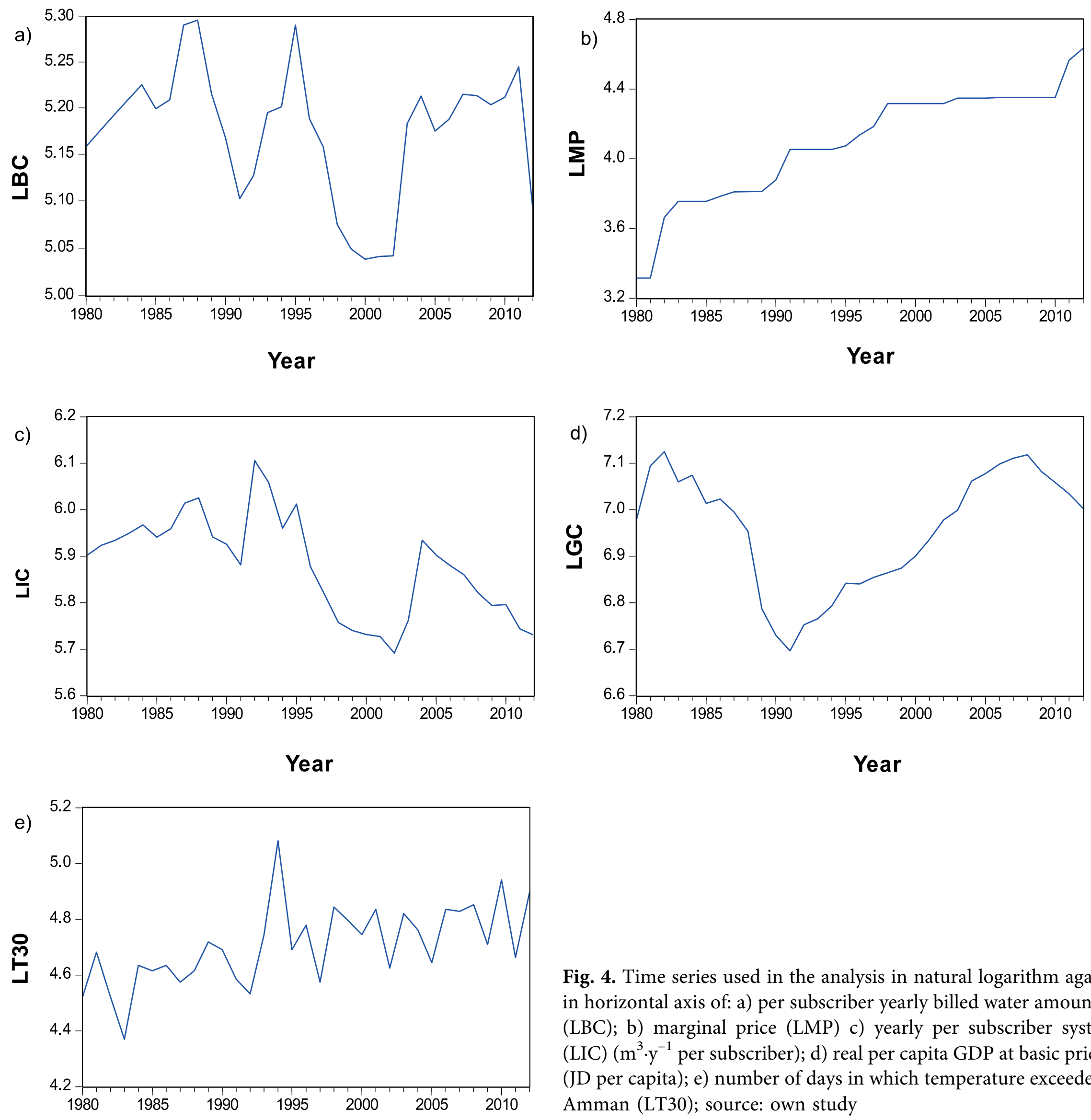

Fig. 4. Time series used in the analysis in natural logarithm against years in horizontal axis of: a) per subscriber yearly billed water amount ($m^3 \cdot y^{-1}$) (LBC); b) marginal price (LMP) c) yearly per subscriber system input (LIC) ($m^3 \cdot y^{-1}$ per subscriber); d) real per capita GDP at basic prices (LGC) (JD per capita); e) number of days in which temperature exceeded 30°C in Amman (LT30); source: own study

Table 1. List of time series used (determinates) and its source and notation

Variable/determinant	Symbol	Source of data
Demand per subscriber account = yearly water use per account ($m^3 \cdot y^{-1}$ per subscriber)	Bc	Miyahuna and Water Authority of Jordan (WAJ)
Marginal price in piaster (100 piaster = 1 Jordan Dinars – JD)	Mp	
System input per subscriber ($m^3 \cdot y^{-1}$ per subscriber)	Ic	
Per capita real GDP at basic prices (JD)	Gc	Central Bank of Jordan and Department of Statistics (DOS) Department of Statistics [2020a]
Number of days temp exceeded 30°C in the year	*T*30	Jordan Meteorological Department (JMD)

Explanations: JD1 = USD1.142.
Source: own elaboration based on listed sources.

Table 2. Descriptive statistics of individual variable

Statistic	Descriptive statistics of individual Variable				
	LBc	LMp	LIc	LGc	LT30
Mean	5.303	4.086	6.008	6.957	4.708
Median	5.326	4.136	5.960	6.995	4.691
Maximum	5.514	4.633	6.318	7.125	5.081
Minimum	5.073	3.315	5.730	6.696	4.369
Standard deviation	0.147	0.327	0.199	0.128	0.143
Skewness	−0.123	−0.650	−0.015	−0.487	0.199
Kurtosis	1.553	2.807	1.310	1.977	3.312
Jarque-Bera	2.960	2.375	3.927	2.744	0.352

Explanations: LBc = per subscriber yearly billed water amount ($m^3 \cdot y^{-1}$), LMp = marginal price, LIc = yearly per subscriber system input, LGc = real per capita GDP at basic prices, LT30 = number of days in which temperature exceeded 30°C in Amman.
Source: own study.

the most literature [AL-NAJJAR *et al.* 2011; CARVER, BOLAND 1980; MARTINEZ-ESPIÑEIRA 2002; NAUGES, THOMAS 2003]. Table 3 lists the effect of the explored variable on water demand in the long and short run as presented in different literature.

Table 3. Proximity of independent variable effect on dependant variable

Independent variable	Notation	Timing of effect on billed amount (*DV*)
Billed amount per subscriber	*Bc*	captures all previous dynamics of the variable
Marginal price	*Mp*	in most cases it is estimated insignificant in both long run and short run
GDP per capita	*Gc*	in most cases it is estimated insignificant in both long run and short run
System input per subscriber	*Ic*	has an insignificant short-run effect
Temperature	*T*30	has a short-run effect, but on the long-run effect it is diminishes

Source: own elaboration based on ARBUÉS *et al.* [2003] and MARTÍNEZ-ESPINEIRA and NAUGES [2004].

A log-log model (natural logs for variables) is used as the relationship suits nonlinear parameters. Variables log transformation generates the desired linearity in parameters which is one of the ordinary least square (*OLS*) assumptions. The natural log enables a straightforward interpretation of the regression coefficients as it represents the elasticity of the dependent variable with respect to independent variable. In other words, the coefficient is the estimated percent change in *DV* for a percent change in the *IV*.

GENERAL FORM OF THE MODEL

The overall approach can be subdivided in a sequence of steps: first is the selection of an appropriate form for the mathematical model, then a diagnostic analysis is performed to check variable stationarity. ARDL technique is used to solve the model and, when the model is statistically acceptable, forecasting is performed.

The general form of the model is initially drafted to include all variables that are expected potentially affect the demand, specifically those included in Table 3. Refinement is made as a result of the analysis. The selected model is multiple-coefficient, non-linear, multiplicative, and logarithmic. With reference to the notations of variable chosen in Table 3, the initial form of the model is described as:

$$c = f(Mp,\ Ic,\ Gc, T30) + \varepsilon \tag{1}$$

$$Bc_t = b_t Mp_t^{\,b_1} Ic_t^{\,b_2} DGc_t^{\,b_3} T30_t^{\,b_5} e^{\varepsilon_t} \quad t = 1, \dots, t \tag{2}$$

Its linear econometric transformed form can be written as

$$\ln Bc_t = b_0 + b_1 \ln Mp_t + b_2\ \ln Ic_t + b_3 \ln Gc_t + b_4 \ln T30_t + \varepsilon_t \tag{3}$$

where: *Bc* is billed amount/subscriber, b_i represent direct elasticities and the error term (ε_t) is assumed to be independently and identically is distributed (iid).

The demand, Bc_t, is expected to be inversely proportional to water marginal price, Mp_t (in piasters, 1 piaster = 1/100 Jordan dinars). Moreover, the demand is expected to be directly proportional to the system input, Ic_t, the number of days in which temperature exceeded 30°C, $T30_t$ and per capita real gross domestic product at basic prices, Gc_t. The system input is included in the model as it is assumed that the demand not fully satisfied, this assumption will be specifically tested. The nominal value of the marginal price is chosen due to the large fluctuations in both inflation and JD–$ exchange rate during the observation period, and to the fact that the customer feels the nominal value, that includes the inflation rate. The above assume that water behaves as a necessary good/service.

UNIT ROOT TESTS

Both augmented Dickey–Fuller (ADF) [DICKEY, FULLER 1979] and Phillips and Perron (PP-1988) [PHILLIPS, PERRON 1988] unit root test is used to check the stationarity of the variables. The null hypothesis of both tests indicates that there is a unit root if the probability value is more than 10% and/or 5% or 1% depends on the level of significance used or if the absolute value of the *t*-statistics is less than critical value at the different level of significance.

Augmented Dickey–Fuller (ADF) and Phillips and Perron (PP-1988) unit root tests were performed in three different forms as follows:
– random walk with drift (constant i.e. intercept),
– random walk with a drift around deterministic time trend (constant and trend),
– random walk (non-deterministic component).

The regression for the ADF of a random walk with a drift around deterministic time trend test is given in the equation below.

$$\Delta Z_t = \alpha_0 + \alpha_1 Z_{t-1} + \alpha_2 t + \sum_{i=1}^{p} \gamma_i \Delta Z_{t-i} + \varepsilon_t \tag{4}$$

where the drift of the variable *Z* over time *t* is presented by a_0, and the time trend is given by the term a_2t. The ε_t component is assumed to be Gaussian white noise random error, and (*p*) number of observations in the sample, time (*t*) varies by *t* = 1, 2 … 32.

ECONOMETRIC MODELLING

Through this study PESARAN and SHIN [1999] and PESARAN *et al.* [2001] procedure has been adopted. In the context of a water demand forecasting, the autoregressive distributed lag (ARDL) model which is an ordinary least square (*OLS*) used. The model solved for prediction of the long-run relationship starting from a dynamic ARDL model.

ARDL co-integration technique is adopted irrespective of whether the underlying variables are stationary on level I(0) or the on first difference I(1), or combination of both and cannot be applied when the underlying variables are integrated at the second difference I(2). ARDL provides a unified framework for testing and estimating of co-integration relations in the constant of a single equation. It is worth mentioning that the ARDL model able to coordinate between the short-run elements and the long-run stability by the development of a dynamic error correction model (ECM) HASSLER and WOLTERS [2006]. The following equation explains the ARDL model:

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \sum_{i=0}^{p} \delta_i \Delta X_{t-i} + \theta_1\, y_{t-1} + \theta_2\, x_{t-1} + \varepsilon_t \quad (5)$$

where: β_i and δ_i present the short-run coefficient, and θ_1 and θ_2 are the long-run ARDL coefficient, while the ε_t is the disturbance (white noise) term.

Now, if θ_1 and θ_2 are not zero, thus there is a conditional level relationship between y_t and x_t. The long-run equation of y_t (equation) and its lagged residuals is expressed by following equations respectively:

$$y_t = \beta_0 + \beta_1 x_t + \mu_t \quad (6)$$

$$z_{t-1} = y_{t-1} - b_0 x_t - b_1\, x_{t-1} \quad (7)$$

Now, the long-run term $\theta_1\, y_{t-1} + \theta_2\, x_{t-1}$ is replace by its residuals (z_{t-1}), therefore, the ARDL reverts to ECM. ECM equation is defined by:

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \sum_{i=0}^{p} \delta_i \Delta X_{t-i} + \theta Z_{t-1}\ + \varepsilon_t \quad (8)$$

where: θ presents the speed adjustment to restore equilibrium in the dynamic model, it is called error correction term (ECT).

Furthermore, to ensure convergence toward equilibrium in the long-run, ECT should be less than zero and significant otherwise, the model is considered unstable and explosive if it is positive.

The ARDL modelling approach to co-integration consists of two steps. First, the long-run relationship between the independent variable and dependent variables is tested. In the next step, the coefficients of the long run are obtained, then by re-parameterizing Equation (5), the ECM is evaluated, and both ECT and the short-run coefficients are estimated. The researcher used EViews Software to analyse the data and to solve the model.

RESULTS AND DISCUSSION

STATIONARITY OF THE VARIABLES

GRANGER and NEWBOLD [1974] indicated in their paper that spurious regression may be obtained by regressing a non-stationary variable on one or more non-stationary variables. This lead to the importance of the stationarity of the variables for a time series regression. In this study, autoregressive distributed lag (ARDL) is used, which has the power to use different time series integrated at different orders. Nevertheless, it shows ineffectiveness when the time series integrated at level two or more [NKORO, UKO 2016].

In this section, the stationarity of billed amount per subscriber (LBc), marginal price in piasters (LMp), system input per subscriber (LIc), per capita real GDP at basic prices (LGc), and the number of days with temperature above 30°C (*LT*30) variables will be checked to ensure the level of integration.

Different tests can be conducted to verify the stationarity of the time series. The famous augmented Dickey–Fuller (ADF) and Phillips and Perron (PP-1988) unit root tests are used [NKORO, UKO 2016; PHILLIPS PERRON 1988]. For the annual data on variables for the period 1980 to 2012, the results of the ADF test and PP test that are performed using EViews software are presented in Table 4.

Noting that the unit root test that EViews provides generally test the null hypothesis H0: $p = 1$ against the one-sided alternative H1: $p < 1$.

The null hypothesis of the tests suggests that the series has a unit root (variable is non-stationary). This hypothesis confirmed if the absolute value of the *t*-statistics is less than critical value at 10% and/or 5% and/or 1% and the probability value is more than 10% and/or 5% or 1% depends on the level of significance used.

On the other hand, the stationarity is confirmed by: (1) *t*-statistics: If the absolute value of the test statistic is greater than the critical values at 1%, 5% and 10% confidence, then this implies statistical significance and the null hypothesis can be rejected which means there is no unit root and the series is stationary; (2) probability (*p*) value acceptable values are less than the confidence level of 10%, 5% or 1%.

Augmented Dickey–Fuller (ADF) test with Schwarz info criterion of max eight lags has been conducted. The test shows that the null hypothesis at the level is acceptable (*p* value > 10%; and the absolute value of the *t*-statistics is less than critical value at 10%, 5% and 1%) for the time series LBc, LMp, LIc, and LGc, which implies the existence of unit root or the variables are non-stationary at level.

For the variable LT30, the test was rejected for intercept and trend and intercept forms; this suggests that the variable is stationary at level (*p* value < 10%; and the absolute value of the *t*-statistics is greater than critical value at 10%, 5% and 1%). While for the non-deterministic component form, the variable shows non-stationarity behaviour see Table 4.

Moreover, the test has been also applied at the first difference of the variables, and the result emphasize that the LBc, LMp, LIc, and LGc, are integrated at the first order (stationary) (*p* value < 1%; and the absolute value of the *t*-statistics is greater than critical value at 10%, 5% and 1%), see Table 4.

Phillips and Perron unit root test shows consistency with the augmented Dickey–Fuller (ADF) test results, in which the variables LBc, LMp, LIc, and LGc, are non-stationary at the level while they are stationary at the first order.

The time series LT30 shows stationarity at the level for random walk with drift and random walk with a drift around deterministic time trend form. Nevertheless, the time series shows non-stationary for random walk.

As a result, all variables show a stationarity behaviour in the first differences I (1) except LT30 which shows stationarity at both levels I (0, 1).

Stationarity has been also tested using correlogram, and Kwiatkowski–Phillips–Schmidt–Shin (KPSS-1992) approaches. Results are analogous to those obtained with the ADF and Phillips and Perron tests.

As a result, all variables show a stationarity behaviour in the first differences I (1). The LT30 variable which shows stationarity at both I (0, 1) should be considered with caution, since it might be I (0, 1).

Table 4. Augmented Dickey–Fuller (ADF) and Phillips and Perron unit root tests

Serie	Level of integration	Parameter	Augmented Dickey–Fuller (ADF) test			Phillips and Perron test			Stationary or non-stationary
			intercept	trend and intercept	none	intercept	trend and intercept	none	
Ln(Bc)	level	*t*-statistic[1]	−2.28	−2.38	−0.24	−2.43	−2.53	−0.25	no
		p value[2]	0.18	0.38	0.59	0.14	0.31	0.59	
	first difference	*t*-statistic	−4.35	−4.26	−4.45	−4.14	−4.05	−4.24	yes
		p value	0.00	0.01	0.00	0.00	0.02	0.00	
Ln(Mp)	level	*t*-statistic	−1.86	−3.17	2.82	−2.05	−3.16	2.92	no
		p value	0.35	0.11	1.00	0.26	0.11	1.00	
	first difference	*t*-statistic	−4.93	−5.04	−3.99	−4.91	−5.02	−4.00	yes
		p value	0.00	0.00	0.00	0.00	0.00	0.00	
Ln(Ic)	level	*t*-statistic	−1.56	−2.52	−0.47	−1.61	−2.58	−0.48	no
		p value	0.49	0.32	0.51	0.47	0.29	0.50	
	first difference	*t*-statistic	−5.62	−5.57	−5.67	−5.62	−5.58	−5.67	yes
		p value	0.00	0.00	0.00	0.00	0.00	0.00	
Ln(Gc)	level	*t*-statistic	−1.92	−2.87	−0.51	−1.44	−1.42	0.04	no
		p value	0.32	0.19	0.49	0.55	0.83	0.69	
	first difference	*t*-statistic	−4.07	−4.19	−4.15	−4.06	−4.18	−4.14	yes
		p value	0.00	0.01	0.00	0.00	0.01	0.00	
Ln(T30)	level	*t*-statistic	−4.36	−6.35	1.58	−4.33	−7.24	1.60	yes
		p value	0.00	0.00	0.97	0.00	0.00	0.97	
	first difference	*t*-statistic	−6.23	−6.27	−5.83	−22.46	−21.34	−19.39	yes
		p value	0.00	0.00	0.00	0.00	0.00	0.00	

The stationarity is confirmed by:
[1] *t*-statistics: If the absolute value of the test statistic is greater than the critical values at 1%, 5% and 10% confidence, then this implies statistical significance and the null hypothesis can be rejected. This means there is no unit root and the series is stationary.
[2] *p* value acceptable values are less than the confidence level of 10%, 5% or 1%.
Source: own study.

Stationarity was also tested using correlogram, and Kwiatkowski–Phillips–Schmidt–Shin (KPSS-1992) approaches. Results are analogous to those obtained with the ADF and Phillips and Perron tests.

OPTIMAL LAG STRUCTURE

An initial unrestricted vector autoregressive (VAR) model has been created to specify the optimal lag length. It links the billed amount per subscriber (LBc) (dependent variable) and other explanatory variable over the running period 1980–2012.

The lag length criteria test has been conducted using three lags (0, 1, 2) to determine the optimal lag length. Different criterion has been tested – see Table 5. The Table 5 shows that the sequential modified log likelihood ratio test statistic (each test at 5% level) (*LR*), Schwarz information criterion (*SC*), and Hannan–Quinn information criterion (*HQ*) suggest that the optimal lag length is one; while the final prediction error (*FPE*) and the Akaike information criterion (*AIC*) go with two lags. We used Akaike's information criterion (AIC) criterion to choose optimal lag lengths for the basic ARDL model.

AUTOREGRESSIVE DISTRIBUTED LAG (ARDL) MODEL

The ARDL model can study the long-run equilibrium relationship between the variables regardless of being I (0) or I (1). For our case, the number of days with temperature above 30°C (LT30) variable is I (0) and I (1) for the intercept and intercept and trend approach; moreover, the rest of the variables are I (1). Therefore, this leads us to propose the autoregressive distributed lag (ARDL) model to study the relation between the billed amount per subscriber (LBc) (dependent variable) and marginal price in

Table 5. Selection lag order/length using different criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	128.0565	NA	2.45e−10	−7.939128	−7.707840	−7.863734
1	239.3987	179.5842*	9.58e−13	−13.50959	−12.12186*	−13.05723*
2	268.3563	37.36462	8.50e−13*	−13.76492*	−11.22075	−12.93559

* indicates lag order selected by the criterion.
Source: own study.

piasters (LMp), system input per subscriber (LIc), per capita real GDP at basic prices (LGc), and the number of days with temperature above 30°C (LT30) (independent variables).

The researcher built the model using the available observations spanned from 1980 to 2012. The model has been estimated using the optimal lag numbers selected by the Akaike information criterion (*AIC*) and from the diagnostic statistics. For the billed amount per subscriber (water demand), the Akaike's information criterion (*AIC*) with automatic lag selection and constant trend specification selects the ARDL (2, 1, 2, 2, 0).

The proposed ARDL model shows a high degree of fit, as measured by the coefficient of determination (R^2) or the corrected coefficient R^2, *F*-statistic, and Durbin–Watson statistics is higher than the R^2. Several diagnostic tests have been implemented which indicates that the obtained ARDL model has no serial correlation and conditional heteroskedasticity and that the errors are normally distributed.

In the first stage of ARDL modelling is testing the presence of co-integration relationship among the determinants, the ARDL bounds technique is used. The results show that the *F*-statistics fall outside the upper limit of critical value bounds. Therefore, the null hypothesis that states there is no long-run relationships exist is rejected; consequently, there are co-integrations among the variables LBc, LMp, LIc, LGc, and LT30 (Tab. 6).

ARDL CO-INTEGRATION APPROACH

Annual data from 1980 to 2012 for Amman were employed to estimate the ARDL approach to co-integration for water demand forecasting as described above. In this section, both long-run and short-run elasticities are estimated, interpreted and compared to international studies. The estimated long-run and short-run coefficients, its standard error and probability are presented in Tables 7 and 8.

Table 6. Autoregressive distributed lag (ARDL) bounds test

Test statistic	Value	*K*
F-statistic [1)]	4.785749	4
	Critical value bounds	
Significance	I0 bound	I1 bound
10%	2.45	3.52
5%	2.86	4.01
2.5%	3.25	4.49

[1)] *F*-statistic of at least 3.95 is needed to reject the null hypothesis at an alpha level of 0.1.
Explanation: *K* = the number of dynamic regressors.
Source: own study.

ARDL LONG-RUN RESULTS

Having established the existence of a long-run equilibrium relationship between the billed amount per subscriber (LBc) and system input per subscriber (LIc) and other explanatory variables, the researcher presents in Table 7 the estimated long-run coefficients. According to the results present in Table 7, both system input per subscriber (LIc), and per capita real GDP at basic prices (LGc) estimates are statistically significant at the 5% level. The estimated long-run coefficients of the marginal price in piasters (LMp) and the number of days with temperature above 30°C (LT30) are not statistically significant.

The results identified that LGc has a significant positive effect on the Lbc, meaning that as the economy becomes more robust, the water consumption increase. If there is an increase of 1% in economic growth, water demand (billed amount per subscriber) will increase by 0.24% in the long-run in Amman.

The estimated coefficient of system input per subscriber (LIc) is positive and highly significant, indicating that more water provided, more water consumed. The long-run system input elasticity of billed amount per subscriber is estimated to be 0.54, implying that a 1% increase in system input will cause about a 0.54% increase in water demand.

The marginal price (LMp) has a negative relationship with the billed amount per subscriber (LBc), while the number of days with temperature above 30°C (LT30) has a positive trend. Nevertheless, both variables have an insignificant relationship in the long-run.

ERROR CORRECTION MODEL (ECM)

Having achieved the long-run elasticities of the billed amount per subscriber equation, an error correction model (ECM) for the selected ARDL Model needs to develop to estimate the short-run elasticities. ECM model has both error correction term (ECT), which presents the speed of the variables returning to equilibrium and short-run coefficients.

Table 8 presents the results of the estimated ECM. ECT estimate is significant with a negative sign. Both system input per subscriber (LIc), and lagged marginal price in piasters (LMp)

Table 7. Long-run elasticities of autoregressive distributed lag model

Variable	C	LGc	LIc	LMp	LT30
Coefficient	−0.01201	0.240586	0.535194	−0.02755	0.053851
Standard error	1.01832	0.070426	0.104818	0.037468	0.073439
T-statistic	−0.0118	3.416158	5.105946	−0.73528	0.733278
Probability (%)	99.07	0.20	0.00	46.83	46.95
R^2			0.56926		
Adjusted R^2			0.507723		

Explanations: LBc = per subscriber yearly billed water amount ($m^3 \cdot y^{-1}$), LMp = marginal price, LIc = yearly per subscriber system input LGc = real per capita GDP at basic prices, LT30 = number of days in which temperature exceeded 30°C in Amman.
Source: own study.

Table 8. Short-run elasticities of autoregressive distributed lag (ARDL) model

Parameter	Variable								
	C	D(LBC(−1))	D(LGC)	D(LIC)	D(LIC(−1))	D(LMP)	D(LMP(−1))	D(LT30)	ECT(−1)
Coefficient	0.004531	0.353947	0.23933	0.467365	0.25322	−0.060759	−0.210611	0.02299	−0.92676
Standard error	0.008506	0.179042	0.188333	0.115798	0.136995	0.093451	0.093521	0.041275	0.193887
T-statistic	0.532644	1.976886	1.27079	4.036019	1.84839	−0.650176	−2.252034	0.55698	−4.77987
Probability (%)	59.96	6.07	21.71	0.06	7.80	52.23	3.46	58.32	0.01
R^2		0.710271							
Adjusted R^2		0.604916							
F-statistic		6.741642							
Prob (*F*-statistic)		0.000175							
Durbin–Watson stat[1)]		2.074471							

[1)] Durbin–Watson stat is greater than 2 indicating negative autocorrelation. Values from 0 to less than 2 positive autocorrelation and values from 2 to 4 indicate negative autocorrelation.
Explanations: D(LBC) = lagged per subscriber yearly billed water amount, D(LGC) = real per capita GDP at basic prices, D(LIC) = yearly per subscriber system input, D(LIC(−1)) = lagged yearly per subscriber system input, D(LMP) = marginal price, D(LMP(−1)) = lagged marginal price, D(LT30) = number of days in which temperature exceeded 30°C in Amman, ECT(−1): the error correction term.

estimates are statistically significant at the 5% level, while the lagged water consumption is significant at the 7%. Moreover, per capita real GDP at basic prices (LGc), the marginal price in piasters (LMp) and the number of days with temperature above 30°C (LT30) are not statistically significant.

Moreover, it was confirmed that the ECM shows a high degree of fit regards the R^2 or the corrected coefficient R^2, *F*-statistic. Durbin–Watson statistics is higher than the R^2 which implies that ECM is not spurious. Likewise, diagnostic tests have been performed to check that the residuals are normally distributed and are neither auto-correlated nor heteroskedastic. The model shows that the residuals are normally distributed and are nor auto-correlated and free of heteroscedasticity.

The parameter associated with the ECM shows how quickly variables converge to equilibrium; this should be significant with a negative sign. The significance of the ECT is an evidence of the stability of the long-run relationship. In our model, the ECT is negative and highly significant, indicating a stable long-term relationship. The water demand model states that LBc restores the long-run equilibrium with a 92.7% speed of adjustment every year by the influence of the variables, LMp, LIc, LGc, and LT30; this implies that the correction takes place relatively rapidly.

The short-run outcomes suggest the lagged water consumption has a significant favourable influence on water demand (billed amount per subscriber) on a 7% level. A 10% increase in water consumption of the previous year will cause a 3.5% increase in water demand in the short run. This result reveals that the water consumption habits play a significant role in current water consumption. This result goes with MARTINEZ-ESPIÑEIRA [2002], NAUGES and THOMAS [2003], MUSOLESI and NOSVELLI [2007], and studies.

Per capita real GDP at basic prices (LGc) has insignificant positive relationships with the water demand. As the per capita real GDP reflect the personal income, this implies that water demand is inelastic to personal income in the short term, this result is quite usual. Nevertheless, the per capita real GDP, as mentioned in section titled "ARDL long-run results", is positive and significant with 0.24% elasticity. Although this value is a little elasticity concerning income, it can give an insight that the water demand is unsatisfied for different level wealth, either by the newly adopted sumptuous lifestyle of rich people or by satisfying more needs by averaged people. Moreover, low water prices exhibit a low level of perception of water consumption value, since a small proportion of income goes for water bills.

The short-run system input coefficient of the billed amount per subscriber is estimated to be 0.47, which means that a 1% increase in system input will lead to about a 0.47% increase in water demand. Moreover, at the 10% level, the lagged system input has a positive association with per subscriber water consumption. The long-run system input elasticity estimate is more abundant in absolute value than the short-run elasticity with a statistically significant point estimate of 0.54 (see section titled "ARDL long-run results"). Although the system input should not affect the water demand, in the case of Jordan, where the water resources are limited, thus the water supply is also limited; this implies that the water demand is not satisfied.

The estimated water price coefficient in the short run is negative and highly insignificant. Moreover, the lagged water price has a significant adverse effect on water consumption, the lagged water price elasticity −0.21, that is low. These estimates of price elasticities, in addition to long-run elasticity, confirm that per capita consumption (billed amount per subscriber) is inelastic to its price. This inelasticity reveals the fact of water shortage, low income, and low water price in the study area. This result is in line with most papers published on residential water demand MARTÍNEZ-ESPINEIRA and NAUGES [2004]), ARBUÉS *et al.* [2010], MUSOLESI and NOSVELLI [2010].

Water demand is positively associated with the number of days with temperature above 30°C (LT30). However, this variable is insignificant in the short and long run (Tabs. 7 and 8). This result suggests that the temperature is not crucial in water consumption estimation, especially in the water-scarce region.

This result suggests that the temperature does not play an essential role in water consumption estimation, especially in the water-scarce region. This result agree with MARTINEZ-ESPIÑEIRA [2002] study.

Generally, the developed model dynamic water demand model in the form of multiple-coefficient, non-linear, multiplicative, and logarithmic is statistically accepted with R^2 of 0.71, this form of modelling has been used by different researchers to represent water demand. Also the model results are in line with internationally reported literature. The results indicate that water demand in limited water resources environment is partially captured in the long run by the amount of water reaching the customer and gross domestic product (GDP). Results show the ability of the model to predicting future trends (short and long-run association). Moreover, the small elasticity of water price and the relation identified between the demand and the water system input with other explanatory variables confirm the condition of water deficit for Amman area and Jordan. Also it can be said that autoregressive distributed lag (ARDL) co-integration modelling provide a suitable empirical tool for predicting water demand using different proposed time series as potential descriptors including per subscriber water consumption, the ARDL approach helps in specifying, estimating and checking the demand model using diagnostic analysis.

CONCLUSIONS

This research developed an autoregressive distributed lag (ARDL) estimator of residential water demand based on Amman area data. Throughout the model, the stationarity of the time series was estimated by different approaches. The model has been verified and proof capable to capture water consumption per user dynamics.

The model developed in this article captures the variations in billed amount per subscriber (water demand) that results from changes in factors affecting the residential water demand. The results obtained of the elasticity values of the variables do match the similar international studies.

Conclusions include that in a country with scarce resources like Jordan, the people do not respond adequately to changes in the water prices directly while the lagged water price has a significant effect on demand. The system input has a highly significant and positive effect on water consumption. This reveals that water usage in Jordan is dominant by the essential needs, and emphasizes that residential water demand is not fully satisfied. The income has insignificant effect in the short-run on water demand, while it is significant in the long run. The lagged water consumption has a positive and significant response to the current water demand. This gives a shred of evidence that habits play essential role in residential water consumption, the results also indicate that number of days with temperature above 30°C, which reflects a climate factor, has insignificant effect on residential water demand in case of poorly satisfied demand situation and low marginal water prices. In other words, the results highlight the priority of satisfying the residential water demand under water shortage conditions while using strategies that depends on variables like water prices, income, and temperature has a low or negligible effect on water demand.

The model provides a tool that can be used by Amman water utility in developing its policies and strategies to cope with future demand in its service area for short- and long-term time horizon.

Other utilities in Jordan and other countries which face similar conditions of water scarcity and arid and semi-arid climate can also base their plans for residential water demand forecasting on the model by tailoring it to suit its specific conditions.

Finally, the autoregressive distributed lag (ARDL) co-integration model estimator can be used by water utilities for develop time series forecasts of residential water demand forecasting.

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