



Specifying a cascade water demand forecasting model using time-series analysis: a case of Jordan

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Abstract

This study aims to develop a model for forecasting water demand for 2021–2030 to examine water availability for municipality uses in the Al-Balqa governorate of Jordan. The method was developed using a time series analysis of historical data from 1990–2010, which comprised yearly and monthly water consumption and socioeconomic factors, including population, income, and climate factors, such as average precipitation and temperatures. The analysis of historical data was conducted using the Statistical Package for the Social Sciences. The study found that the increase in population, reaching 740,790 inhabitants in 2030, the high level of social life, and the fluctuation of temperature and precipitation exceed the significant water demand, increasing to 69.88 million cubic meters in 2030 from 52.95 in 2020. The time series analysis employed historical data for 2011–2020 indicating monthly municipal water use to measure the model's validity. The results confirm the model's ability to forecast water demand. The study recommends intensifying managerial practices to avoid such difficulties that face the water sector to achieve water security at the country's level.

Keywords Water demand forecasting · Historical data · Time series analysis · Al-Balqa governorate · Jordan

Introduction

Water is the most critical natural resource that plays a key role in the growth of all economic sectors (Chaplin 2001). Water is not only vital for human life, which is seen by many as a right but also a unique social and economic good, service, and crucial link between humans, the environment, and the economic system (Alissa 2007). Furthermore, climate change is likely to significantly influence the availability of freshwater resources (Matta et al. 2022a). In addition, with uncontrolled population growth, industrialization, and urbanization, water scarcity faces many parts of the world. As a result, the situation worsens, leading to continued environmental degradation and climate change globally (Bond et al. 2019; Matta et al. 2022a), which results in excessive

freshwater demand, especially in emerging countries (Matta et al. 2022b). Moreover, severe problems affect societies, including water pollution, availability, and quality of freshwater for basic needs (Matta et al. 2022b). In this regard, the United Nations (UN) encourages sustainable development, which is key to securing a sufficient quality of life for the coming generations without threatening the present population's needs (WCED 1987).

In 2015, the UN declared the 2030 Agenda, which provides a blueprint strategy that includes 17 Sustainable Development Goals (SDGs) and requires urgent calls for action by developed and developing countries with main support to low-income countries as a global partnership (UN 2015). As a developing country, Jordan sees water as a critical natural resource that plays a central role in connecting social, economic, and political issues with national security (Alissa 2007). However, Jordan faces complex developmental challenges related to the following: continuing water scarcity, climate change, geographical location, the interaction between low average precipitation with some successive years of drought, population growth, improvements in living standards, growth in economic activity, and the region's political environment (ME 2021; World Bank

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2022). In particular, Jordan is considered one of the most water-stressed countries in the world (Alissa 2007).

Jordan is located in an arid to semi-arid zone, having various weather conditions and hydrological elements, such as rainfall, runoff, and evaporation. These factors differ daily from summer to winter and year to year and cause water limitations (Alissa 2007; Abdel Khaleq 2008). The annual rainfall is less than 200 mm, with over 92% of the land being desert (Alissa 2007; Word Bank 2021). Water resources available per capita are limited and continually dropping because of unexpected population growth due to regional instability during the last decade. This phenomenon increases the water demand, impacting Jordan's plan for balancing water demand and supply significantly (Abdel Khaleq 2008). Water scarcity poses a serious challenge affecting the well-being, security, and economic future of all Jordanians (Alissa 2007; Ministry of Water and Immigration (MWI) 2011). Indeed, a critical imbalance remains between supply and demand, particularly in the context of regional insecurity and the social, economic, and environmental impacts (Alissa 2007).

Jordan is fully aware of the importance of providing drinking water for people while the gap between supply and demand is still evident, resulting in a significant water deficit. With its World Water Development Report 2020, the UN emphasized the current and future challenges and encouraged possible responses to climate change conditions that enable the adoption of water demand management practices (Matta et al. 2022b). As a result, the Jordanian government continues to adopt management practices to decrease this gap, involving several programs, projects, and managerial measures for conserving water, and reaching a high level of water supply for its citizens (Alissa 2007; MWI 2011).

Moreover, such developments thus significantly affect water supply for domestic and non-domestic uses. Almost 94% of Jordanians have access to safe drinking water (MPIC 2017; MWI 2011). However, the daily per capita water consumption is low, 74.7 L/person/day, and the government is working to raise this to approximately 122.6 L/person/day by 2030 (MPIC 2017). Despite 97% of Jordanians having access to safe drinking water, the water deficit is apparent in that the per capita water supply is insufficient to meet overall requirements. As a result, Jordan's government has stated that the water supply will not meet demand safely in 2030 (MWI 2011). Notably, illegal water usage is a major issue affecting water supply for domestic and non-domestic needs (Abdel Khaleq 2008; Alissa 2007; MWI 2011; Word Bank 2021).

No single action can address the water shortage, but several actions can improve overall water availability so that future water needs can be met (MPIC 2017; MWI 2011). The relationship between water demand and supply must be understood. Therefore, a forecast of the water demand

is needed with the development of Jordan's activities and rapidly increasing population since the current water supply is insufficient. As a result, water demand forecasting is crucial for an efficient plan for water, reallocating among uses and sectors, and establishing good water governance. This strategy could be implemented to reduce the imbalance between demand and supply in Jordan.

Literature review

The increased value of water for municipal purposes is due to population growth and improvements in economic standards and lifestyles. This rise in water demand is considered a challenge confronting policymakers (Memon 2021; MPIC 2017; MWI 2011). Therefore, forecasting water demand based on historical water usage data is crucial to determining the availability of water in the future and how to influence water usage (Memon 2021).

Water demand forecasting can be conducted based on probabilities, i.e., using a scientific foundation and previous information to estimate water availability in the future (Memon 2021). However, the probable results give only an indication of the expected demand for water consumption. The main purpose of forecasting is to limit the gap between the water reality and future usage, enabling decision-makers to provide for the needs and devise alternatives (Mays and Tung 1992; Memon 2021).

Indeed, many factors influence water usage, such as population, economic factors, weather, and lifestyle. Therefore, the trends of decision-makers can be controlled by forecasting the various water needs and available quantities to obtain an optimal, realistic strategy (Mays and Tung 1992). While future water needs are related to the basic element of population growth, connecting this element with consumption only leads to imprecise results in terms of forecasting water consumption. In addition to population growth, other factors are present, such as lifestyle progression and the increase in consumer awareness. As a result, some natural disturbances, or political events, such as wars and immigration, can increase water demand. The reliance on demographics can yield errors in forecasting due to sudden events or the lack of knowledge relating to these factors (Mays and Tung 1992). Therefore, forecasting water demand enables decision-makers to set alternative methods to provide water resources through various studies. As a result, future water demand can be evaluated through changeable circumstances, improving the efficiency of forecasting (Lawgali 2008).

After reviewing literature from across the world, few research papers have studied forecasting using a proactive approach, which creates or controls a situation by causing something to happen rather than reacting to an event. However, Abdallah (2010) applied a proactive approach to

establish a model to study the differences in water use. The study's samples included 14 cities and tourist areas in Jordan in 2007. The model used various statistical methods and correlated the general consumption of water with seven levels of consumption. The study predicted the future water needs for touristic activities in Jordan. The results showed that the future demand for water for touristic purposes would increase, reaching ten million cubic meters (10 MCM) in 2020.

In a similar study, Mohamed and Al-Mulla (2009) conducted research on forecasting water demand for the subsequent 25 years in Umm-Al Quwain (UAQ), located in the northern part of the United Arab Emirates, using the IWR-MAIN software through a database comprising annual water consumption since 1980 and monthly consumption since 2000. The authors derived a mathematical model to predict the future water reality. The population of UAQ, average temperature, and average rainfall were the independent variables that were correlated with water consumption. The data from both databases were divided into two periods, namely, a regression period and a calibration period. The Statistical Package for the Social Sciences software (SPSS) was used to determine the correlation coefficients between the independent variables and actual water consumption for the regression period. The researchers input these coefficients in IWR-MAIN over the calibration period to calculate water demand, which was compared against actual water consumption. The results predicted a 50% increase in water demand in 2015 and double the current demand by 2025, owing to the population increase due to the rising migration rates to UAQ because of the new developments.

In other research, Al-Dorgham (2008) aimed to use various tools that estimate the size of used water quantities in the agricultural sector and forecast water demand in the Jordan Valley. The results were compared to the actual demand to verify the method's efficiency and ability to use the appropriate tools through the data and the calculations.

Furthermore, Lawgali (2008) carried out a study to determine the future water demand for agricultural, industrial, and domestic use in Libya until 2020. The author employed the Box–Jenkins to forecast the water demand for all purposes using annual data regarding Libyan water from 1975 to 2005. In the United States, Balling and Gober (2006) studied climatic variables and residential water use in Phoenix, Arizona. They investigated how the city's annual water use was influenced by climatic variables between 1980 and 2004. They developed simple correlations between water use and annual mean temperature and total annual precipitation. Results showed that statistically significant relationships were present between climatic conditions and water use in Phoenix. In addition, for every 1 °C temperature increase/decrease in mean annual temperature, an increase/decrease of 60.76 Liter per capita per day of consumed water

occurred. Finally, a simple regression equation for total annual precipitation showed a 10 mm decrease/increase in precipitation would increase/decrease water usage by only 4 Liter per capita per day.

In Mecca, Saudi Arabia, Almutaz et al. (2012) developed a model to forecast water demand for this holy land based on historical data from 2003 to 2011, including water consumption, local population, population growth, number of visitors, household size, average household income, and temperature. These data were split into forecast (between 2003 and 2008) and validation (between 2009 and 2011) datasets. Studying the same geographic area, Ajbar and Ali (2015) conducted a study to forecast municipal water for arid countries, including Saudi Arabia. This study developed a neural network model to forecast the monthly and annual water demand for Mecca. The proposed model used historical data to calibrate a neural network model for water demand forecasts. The variables included the household income, persons per household, city population, expected number of monthly visitors, and maximum monthly temperature. The researcher concluded that achieving the desired prediction was challenging since the forecast model should consider a variety of factors, such as economic development, climate conditions, and population growth.

Previous studies have shown concern about agricultural water demand forecasting, while few studies were conducted regarding municipal water use. The current research paper focuses on forecasting water demand for domestic use only for the municipality sector for 2021–2030 to examine the availability of water use in the Al-Balqa governorate. However, most of the reviewed literature only considered economic and policy factors characterized by a known future evolution. Few focused on weather factors, which have an uncertain evolution. Therefore, additional models and methodologies are needed to assess the effects of climatic factors for short- and medium-term scenarios, as is the aim of the current research.

Methodology

In the current research, three phases were carried out to develop a water demand forecasting model for 2021–2030, as shown in Fig. 1.

In **Phase I**, an extensive literature review was conducted to determine the gap that the current research seeks to fill. In addition, the model formulation stages were reviewed according to various studies, especially the study conducted by Mays and Tung (1992), to develop the model for forecasting water demand. Therefore, a key element of this research is the set of variables used to build the mathematical model that can make predictions based on a time series of historical data (Leith 1973). As a result, an effective model can

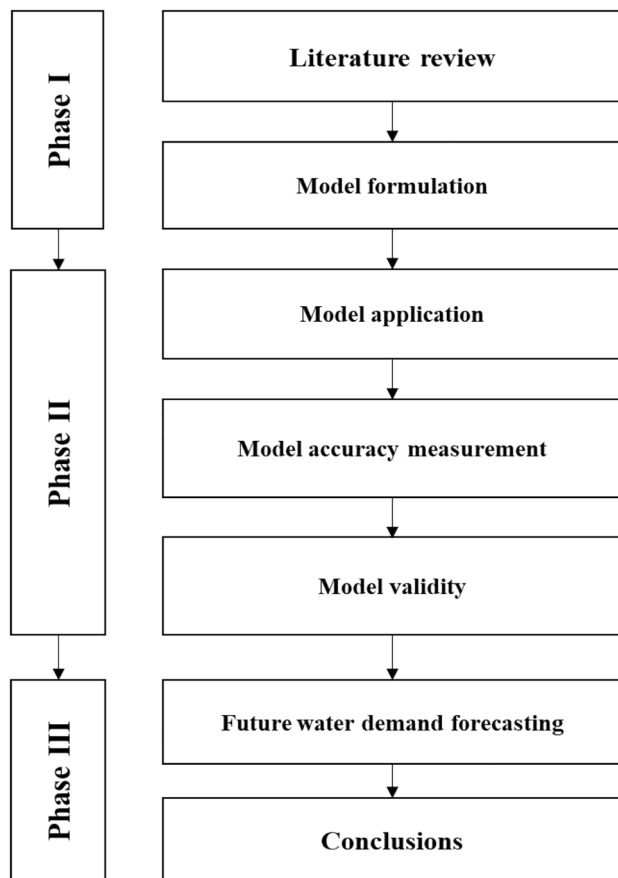


Fig. 1 HYPERLINK "sps:id::fig1|locator::gr1|MediaObject::0" Research methodology

provide actionable information for decision-makers, such as water demand predictions.

In **Phase II**, several data were collected, including population, precipitation, temperature, and personal income from 1990–2010 and then 2011–2020. The data collected from various governmental sources was published for the public using documentary data and obtained by the authors. This phase comprised three phases: model formulation, model accuracy measurement, and model validation. The authors of this work used a statistical method to develop a forecasting model by time series analysis. This method can provide tools for model selection that can be used to predict future events, such as supply and demand for a particular good or service (Leith 1973). At this phase, the model accuracy was measured using the data for 1990–2010. Then, to validate the model, three tasks were carried out: measurements of the standard errors of estimates, sensitivity analysis, and lastly, semi-structured interviews of experts.

In **Phase III**, the model developed in Phase II was applied to forecast water demand for 2021–2030. To this end, a time series analysis was used to forecast municipal water needs. A time series analysis applies a set of ordered, recorded, and

observed measures for one or more variables for a certain phenomenon according to the time of its occurrence. Time series is a series of observations of a phenomenon within a specified period (Jaber and Mohsen 2020). The use of appropriate time series data is considered an accurate and precise method of forecasting for specific timeframes. Valuable time series data that are often used for forecasting are those concerned with demographic and economic issues and those concerned with company profits (Mays and Tung 1992). An accurate forecast for each year reflects the extent of concern and allows potential problems to be avoided (Jaber and Mohsen 2020).

Indeed, a time series analysis is needed to monitor phenomena and observe changes within a certain time. Eventually, the time series analysis can be used to forecast from historical data based on the variables in the time series and the extents of their changes (Jaber and Mohsen 2020). On the other hand, the traditional method takes only two-time series data points, then measures the difference in value between them to build a prediction for the future. This is conducted without considering the general pattern of the time series and the extent of the overall change in values (Leith 1973). In the current research, the historical data used for water demand forecasting in the Al-Balqa governorate include population, monthly and yearly precipitation, annual family income, and monthly temperature.

Study area: Al-Balqa governorate in Jordan

The current research employed data collected from the Al-Balqa Governorate in Jordan. These data are related to lifestyle progression, the demographic factor that leads to population increase, and seasonal patterns, such as average monthly and yearly precipitation and temperature from 1990 to 2010. The shortage of water is a significant problem that the Al-Balqa governorate faces. In addition, the fluctuation of precipitation in the Al-Balqa governorate is a primary factor affecting the water situation, along with the lack of awareness among the population regarding the use of water demand for domestic purposes. Moreover, the gap between supply and demand continues to grow, which results in increased water shortages. This gap is caused by the limited water resources, noneconomic domestic use of water, and the impact of low fees on water use in the municipal sector. As shown in Fig. 2, Al-Balqa Governorate is in the western part of Jordan, covering 1120.4 km² and constituting 1.3% of the total area of the country (MOI 2021). The Al-Balqa governorate represents an average location in Jordan. Many adequate basic services are available, such as healthcare, cultural centers, and sports. The country's main activities are concentrated in agriculture, especially in the Jordan Valley and its affiliates. The Al-Balqa governorate is a strategic and

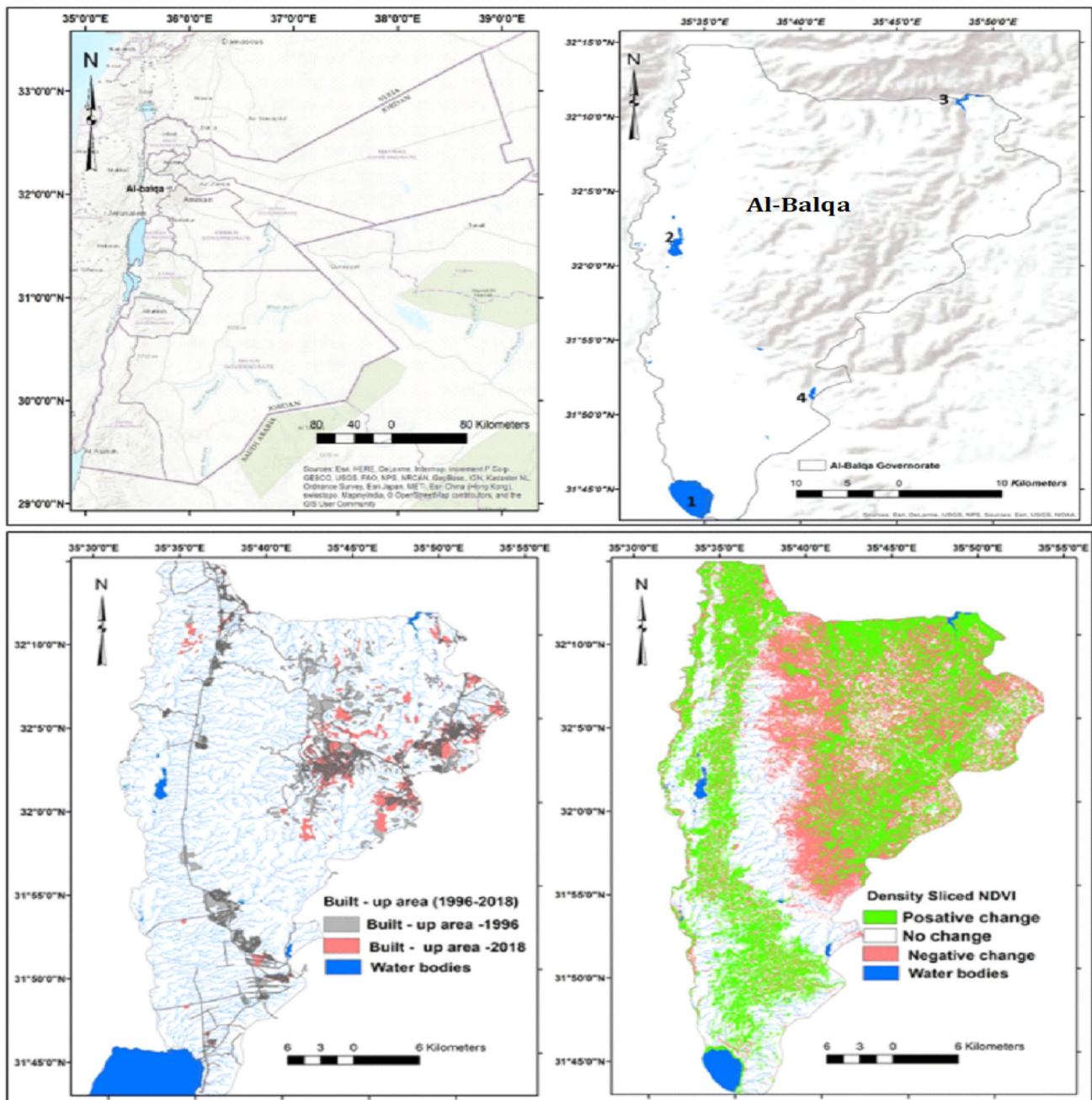


Fig. 2 Al-Balqa governorate map (MOI 2021)

developed location in Jordan, only 29 km from the capital, Amman, and 350 km from Aqaba (MOI 2021).

The governorate maintains the diversity of climate and terrain and is divided into two semi-equal divisions: the highlands and the Jordan Valley. The Jordan Valley reaches 424 m below sea level, and the mountains reach an elevation of 1130 m. The high areas have a rainy climate, cold winter, mild summer, and average precipitation of

600 mm, while the low areas (Jordan Valley) are characterized by moderate winter temperatures, high summer temperatures, and an average rainfall of 150–200 mm (MOI 2021). The different climates allow the governorate to maintain agricultural diversity throughout the year, as well as tourism in winter and summer. The water network covers almost all the communities in the governorate, feeding from 31 working artesian wells (MOI 2021).

Water demand forecasting stages

Historical patterns can be determined by time series data of monthly municipal water use and, thus, divided into long- and short-run components of memory (Leith 1973). Long-term memory components can be classified into two subcomponents (Mays and Tung 1992). The first is a trend that indicates the yearly effect of slow change in variables such as population, annual family income, and yearly precipitation. The second component, seasonality, indicates the cyclic pattern of water use within a selected year. The short-term components can also be classified into two subcomponents (Mays and Tung 1992). First, autocorrelation indicates the departure of water usage from the long-term pattern. Second, a climatic correlation indicates the effect on water use within exceptional climate conditions (dry or wet years).

Detrending

At this stage of developing the model for the cascade prediction of water demand, the trend of the annual mean of monthly water uses in each year $Q_a(y)$ is calculated, and it is related to variables such as population, income, and yearly precipitation in Eq. 1:

$$Q_a(y) = \eta_0 + \eta_1 \times Population(y) + \eta_2 \times Income(y) + \eta_3 \times Precipitation(y) \tag{1}$$

where $\eta_0, \eta_1, \eta_2,$ and η_3 are regression coefficients and y is the year.

Next, the trend value obtained from Eq. 1 is subtracted from the measured monthly water use $Q_a(m,y)$ to describe the detrending using time series, as in Eq. 2:

$$Q_b(m,y) = Q_a(m,y) - Q_a(y) \tag{2}$$

where $Q_b(m,y)$ is the detrended monthly water use, and m is the month.

Deseasonalization

The deseasonalization stage uses the detrended series $Q_b(m,y)$ to determine the seasonality pattern using the fitting monthly average in $Q_b(m,y)$. The yearly seasonality can be characterized by $Q_b(m)$, where $m = 1, 2, \dots, 12$ using Eq. 3:

$$Q_b(m) = \frac{1}{Y} \sum_{y=1}^Y Q_b(m,y) \tag{3}$$

with Eq. 4, the seasonality can be found:

$$Q_b(m) = \sum_{k=0}^6 \left[a_k \cos\left(\frac{2\pi km}{12}\right) + b_k \sin\left(\frac{2\pi km}{12}\right) \right] \tag{4}$$

where a_k and b_k are the Fourier coefficients per Eqs. 5a, 5b, and 5c.

$$a_0 = \frac{1}{12} \sum_{m=1}^{12} \left[\frac{1}{Y} \sum_{y=1}^Y Q_b(m,y) \right] \tag{5a}$$

where Y is the total number of years.

$$A_k = \frac{1}{6} \sum_{m=1}^{12} \left[\frac{1}{Y} \sum_{y=1}^Y Q_b(m,y) \right] \cos\left(\frac{2\pi km}{12}\right) \tag{5b}$$

for $k = 1, 2, \dots, 6$

$$A_k = \frac{1}{6} \sum_{m=1}^{12} \left[\frac{1}{Y} \sum_{y=1}^Y Q_b(m,y) \right] \sin\left(\frac{2\pi km}{12}\right) \tag{5c}$$

for $k = 1, 2, \dots, 0.6,$ and $b_0 = 0.$

The seasonal pattern is removed from $Q_b(m,y)$ to illustrate the deseasonalized series, using Eqs. (3, 4), then Eq. 6 can be obtained as follows:

$$Q_c(m,y) = Q_b(m,y) - Q_b(m) \tag{6}$$

Autoregressive filtering

Autoregressive filtering removes the autocorrelation based on the equation $Q_c(t) = Q_c(m,y)$, where $t = 1, 2, \dots, T$, and then using Eq. 7:

$$Q_c(t) = \sum_{i=1}^I \Phi_i Q_c(t - i) + Q_d(t) \tag{7}$$

where t is the month number from the start of the time series to the last month T and Φ_i is the autoregressive coefficient, determined using Eq. 8 through a linear regression analysis:

$$Q_c(t) = \Phi_0 + \Phi_1 Q_c(t - 1) \tag{8}$$

Values of $Q_c(t)$ from the seasonality can be used to find the residual $Q_d(t)$, where $t = 2 \dots, T$ in Eq. 7.

Climatic regression

To compute the dependence of monthly water use related to time series from the autoregressive analysis variable $Q_d(t)$, the climatic variables of the same month t where $t = 1, 2, \dots, T$ is presented in Eq. 9 as follows:

$$Q_d(t) = \sum_{l=1}^L \beta_l x_l(t) + Q_e(t) \tag{9}$$

where x_l is the l th climatic factor, L is the total number of climatic factors, and β_l is the regression coefficient, Values of β_l and $Q_e(t)$ are determined through a linear regression analysis using the values of $Q_d(t)$ found from the auto-correlation

stage. To use the cascade time series model to forecast water demand, data need to be collected from the authorities related to water. Thus, based on the historical data of monthly municipal water consumption for the Al-Balqa governorate from 1990–2010, a time series analysis can be used to build a forecasting model. This model involves four stages in long-term components $Q_L(t)$ or $Q_L(m,y)$ and short-term components $Q_S(t)$ or $Q_S(m,y)$ to obtain monthly municipal water use in the Al-Balqa governorate. And it can be expressed as $Q(t)$ for $t=1, 2, \dots, T$ or $Q_a(m,y)$ for $m=1, 2, \dots, 12$ and $y=1, 2, \dots, Y$, where m is the month for each year, and y is the number of years since the beginning, and Y is the total number of years in the study.

Figure 3 shows the monthly municipal water consumption from January to December from 1990–2010. Of note, the monthly water consumptions $Q_a(m,y)$ from June to September are higher than the other months, owing to the high temperature and additional uses during summer. The lowest monthly water consumption is at the beginning and end of the year because of the typically decreased use during winter.

Model formulation of water demand forecasting of the Al-Balqa governorate

The current study employs a cascade model in the analyses of historical data. Specifically, this cascade model indicates two successive development stages that are involved in transforming monthly water demand using time series analyses by four sequential stages (Mays and Tung 1992). The following stages are used to forecast water demand in the Al-Balqa governorate.

Detrending

The detrending analysis is the first stage in the cascade model development. The trend of monthly municipal water use over a year is identified in the historical time series. This estimated trend is removed to assess the water use trend over the years, such that $Q_a(y)$ represents the annual mean of monthly water use in year y as calculated in Eq. 10:

$$Q_a(y) = \frac{1}{12} \sum_{m=1}^{12} Q_a(m,y) \quad (10)$$

where $y=1, 2, \dots, Y$. Table 1 lists the annual mean of monthly water use $Q_a(y)$ and monthly municipal water use $Q_a(m,y)$ from 1990–2010. The minimum value of water use was 1.14 MCM in 1990, and the maximum value of 2.31 MCM appeared in 2010. Thus, the general trend for the annual mean of monthly water use $Q_a(y)$ is increasing from 1990–2010 (MWI 2011).

Figure 4 shows the annual mean of monthly municipal water use $Q_a(y)$ in the Al-Balqa governorate from 1990–2010 (MWI 2011). The annual mean in high elevations increased during 1990–1994 and dropped in 1995–2001. However, from 2001–2002, the monthly water use significantly increased, then dropped slightly in 2003, but returned to a noticeable rise from 2004–2010 because of population growth. This factor is evident in the increase in water consumption from 1990–1995 with the rapidly growing population in Al-Balqa governorate caused by the political crises in the region of the Refugees to the Middle East. In 2001, water consumption slightly dropped after the new law of the municipality was issued, which encouraged water harvesting in households and water-saving fittings for reduced water use.

Fig. 3 Monthly municipal water use for 1990–2010 (MCM)

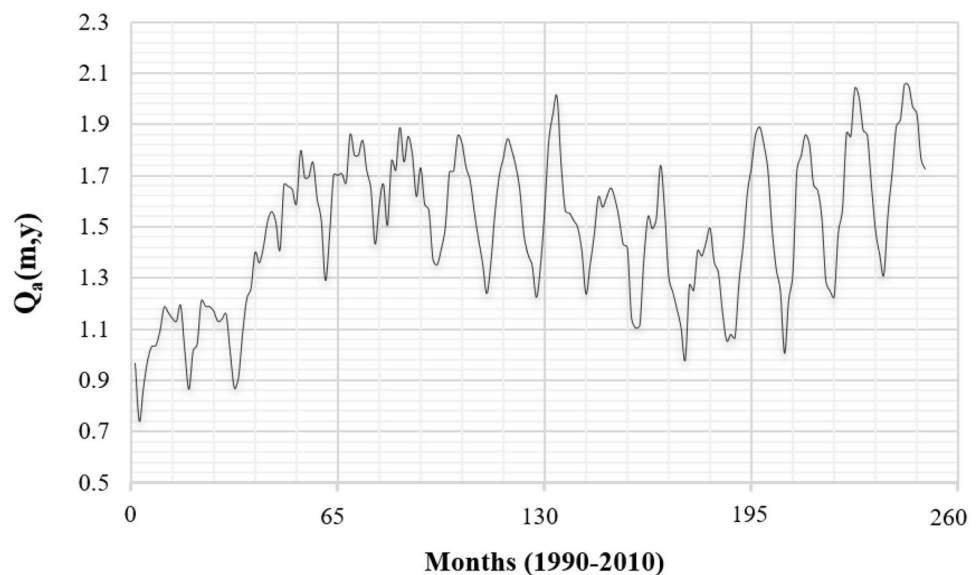


Table 1 Total yearly and annual mean of monthly water use

| Year | Total annual demand of water MCM* | $Q_a(y)$ MCM |
|------|-----------------------------------|--------------|
| 1990 | 13.66 | 1.14 |
| 1991 | 14.31 | 1.19 |
| 1992 | 16.97 | 1.41 |
| 1993 | 21.08 | 1.76 |
| 1994 | 22.2 | 1.85 |
| 1995 | 22.19 | 1.85 |
| 1996 | 20.96 | 1.75 |
| 1997 | 20.66 | 1.72 |
| 1998 | 20.96 | 1.75 |
| 1999 | 19.53 | 1.63 |
| 2000 | 17.92 | 1.49 |
| 2001 | 16.66 | 1.39 |
| 2002 | 20.16 | 1.68 |
| 2003 | 19.88 | 1.66 |
| 2004 | 22.12 | 1.84 |
| 2005 | 21.28 | 1.94 |
| 2006 | 23.54 | 1.96 |
| 2007 | 23.81 | 1.98 |
| 2008 | 23.38 | 1.95 |
| 2009 | 25.2 | 2.1 |
| 2010 | 27.69 | 2.31 |

*Yearly Reports of MWI for 1990–2010 (MWI 2011)

Long-term water use in the Al-Balqa governorate is related to socioeconomic factors, such as population, annual family income, and annual precipitation. Thus, the annual mean of monthly water use can be computed using Eq. 1, where $y = 1, 2, \dots, 16$, and the average total annual demand

of water is considered the dependent variable $Q_a(y)$ in Eq. 1. The annual mean of monthly water use accounts for three socioeconomic effects using the coefficients η , which can be estimated by regression analysis based on the historical data of monthly water use $Q_a(y)$ in Table 1 and socioeconomic factors in the Al-Balqa governorate from 1990–2010, as listed in Table 2. The annual growth of population and annual family income increased from 1990–2010, but a fluctuation in annual precipitation occurred over the same period.

In Eq. 1 for this scenario, $Q_a(y)$ is the monthly mean of water use in (MCM) in year y , $Population(y)$ is the thousands of inhabitants in the Al-Balqa governorate in year y , $Income(y)$ is the area’s average household income in Jordan Dinar (JD) in year y , $Precipitation(y)$ is the total amount of precipitation in year y , and η_{0-3} are model parameters to be estimated by regression analysis using SPSS.

Because the three independent variables are expected to affect the dependent variable for the water use trend model, multiple regression can be performed using SPSS based on 21 years of historical observations to estimate the model parameters $\eta_0, \eta_1, \eta_2,$ and η_3 . The results of the regression are shown in Table 3.

Once the model parameters are estimated, as shown in Table 3, they can be used in Eq. 1 to calculate the average monthly water use $Q_a(y)$ in MCM for 1990–2010, as shown in Table 4. Of note, the estimated $Q_a(y)$ values are not close to the measured $Q_a(y)$ values, so additional parameters affecting the annual average monthly municipal water use need to be determined.

Equation 2 for determining the annual water consumption trend $Q_b(m, y)$ is effective in predicting water consumption related to model parameters. For the scenario

Fig. 4 Annual mean of monthly municipal water use for 1990–2010

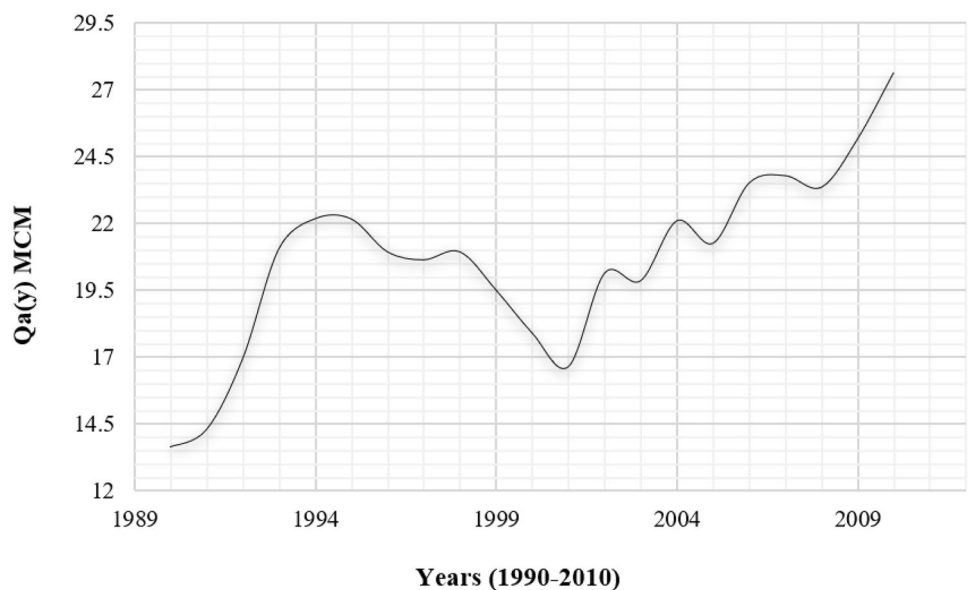


Table 2 Population, annual income, and precipitation for 1990–2010

| Year | Population *(Thousand) | Avg. annual income (JD)** | Annual precipitation*** (mm) |
|------|------------------------|---------------------------|------------------------------|
| 1990 | 231.32 | 476.9 | 286.05 |
| 1991 | 246.86 | 508.31 | 665.1 |
| 1992 | 256.4 | 539.72 | 691.65 |
| 1993 | 266.33 | 571.13 | 239.65 |
| 1994 | 276.1 | 602.54 | 647.9 |
| 1995 | 284.4 | 633.95 | 175.05 |
| 1996 | 292.3 | 665.36 | 394.15 |
| 1997 | 300.5 | 696.77 | 515.35 |
| 1998 | 308.4 | 728.18 | 252.5 |
| 1999 | 316 | 759.59 | 190.5 |
| 2000 | 325.4 | 791 | 461.15 |
| 2001 | 333.5 | 822.41 | 321.85 |
| 2002 | 341.6 | 853.82 | 587.65 |
| 2003 | 350.4 | 885.23 | 499.05 |
| 2004 | 356 | 916.64 | 369.7 |
| 2005 | 367.2 | 948.05 | 425.15 |
| 2006 | 375.2 | 979.46 | 396.15 |
| 2007 | 383.4 | 1010.87 | 368.35 |
| 2008 | 391.9 | 1042.28 | 251.6 |
| 2009 | 400.6 | 1073.69 | 448.55 |
| 2010 | 409.5 | 1105.1 | 293.85 |

*, **, ***Yearly reports from the Department of Statistics for 1990–2010 (Department Of Meteorological 2011)

Table 3 Regression coefficients

| Coefficients | Value |
|--------------|---------|
| η_0 | -4.4925 |
| η_1 | 0.0525 |
| η_2 | -0.0137 |
| η_3 | -0.0003 |

Table 4 Average monthly water use

| Year | Q_a (y) MCM | Year | Q_a (y) MCM |
|------|---------------|------|---------------|
| 1990 | 1.03 | 2001 | 1.65 |
| 1991 | 1.3 | 2002 | 1.57 |
| 1992 | 1.37 | 2003 | 1.63 |
| 1993 | 1.59 | 2004 | 1.53 |
| 1994 | 1.55 | 2005 | 1.67 |
| 1995 | 1.7 | 2006 | 1.96 |
| 1996 | 1.62 | 2007 | 1.98 |
| 1997 | 1.58 | 2008 | 1.95 |
| 1998 | 1.65 | 2009 | 2.1 |
| 1999 | 1.63 | 2010 | 2.31 |
| 2000 | 1.62 | – | – |

in Jordan, $y = 1990, 1991 \dots 2010$, and $Q_a(y)$ is the annual water use trend expressed by removing the trend found in the historical monthly water use time series $Q_a(m, y)$. The detrended monthly water use time series $Q_b(m, y)$ can be obtained using the monthly average of water use $Q_a(m, y)$ in Table 1 and the estimated average of monthly water use in Table 4.

Figure 5 shows the detrended monthly water use time series variable $Q_b(m, y)$ for 1990–2010. The scatter is reduced for the monthly water use after performing the detrending of the original data $Q_a(m, y)$ using Eq. 2. Final results using SPSS show that the detrended monthly water use time series $Q_b(m, y)$ has a mean of 0.085 MCM and standard deviation (SD) of 0.385. The SD is a widely used measure of variability or diversity from the mean value. Since, in this case, the SD is less than that of $Q_a(m, y)$, which was 0.42, the dispersion was reduced.

Deseasonalization

Deseasonalization is the second stage in analyzing the long-term historical components. The detrended monthly water use time series $Q_b(m, y)$ contains a seasonal water use pattern that should be removed. To account for seasonality in water use in the detrended monthly water use time series $Q_b(m, y)$, the arithmetic mean $Q_b(m)$ is calculated for each month within a year using Eq. 3:

$$Q_b(m) = \frac{1}{Y} \sum_{y=1}^Y Q_b(m, y) \tag{3}$$

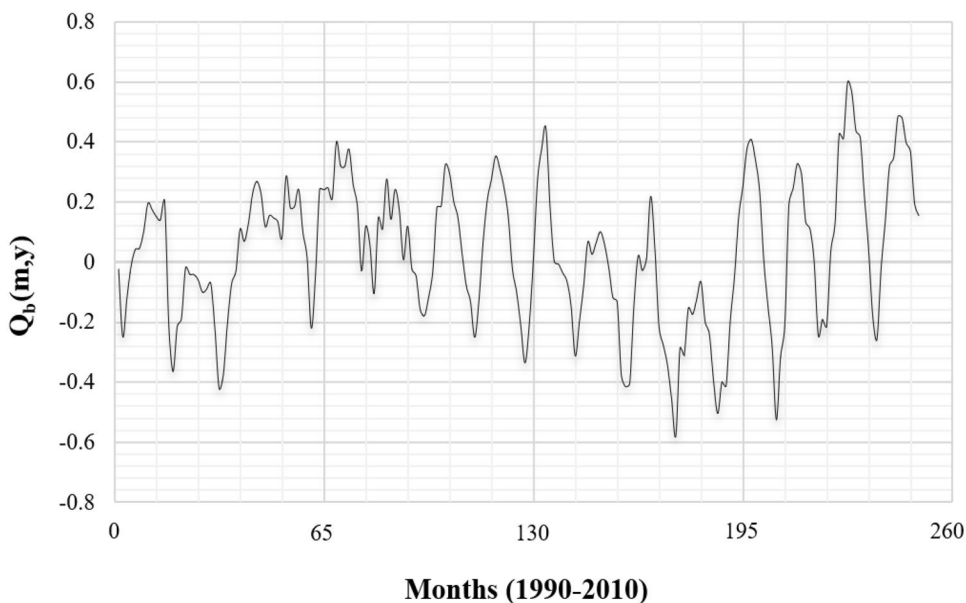
$\frac{1}{Y} \sum_{y=1}^Y Q_b(m, y)$ where the month $m = 1, 2, \dots, 12$ and $Q_b(m, y)$ is the detrended monthly water use time series (MCM), and $Q_b(m)$ is the arithmetic mean (MCM).

Since the seasonality is assessed and accounted for in the monthly water use time series, it can be modeled as periodicity using a Fourier series to determine the monthly seasonal water use pattern, as shown in Eq. 4 (Mays and Tung 1992).

$$Q_b(m) = \sum_{k=0}^6 \left[a_k \cos\left(\frac{2\pi km}{12}\right) + b_k \sin\left(\frac{2\pi km}{12}\right) \right] \tag{4}$$

where the month $m = 1, 2, \dots, 12$, the Fourier coefficients a_0, a_k , and b_k can be determined using Eqs. 5a, 5b and 5c (Mays and Tung 1992). In general, the first six harmonics of a periodic parameter are sufficient and can be tested for significance. All harmonics beyond the sixth harmonic provide only a relatively small additional explanation of the variance of the estimated value (Mutreja 1986).

Fig. 5 Detrended monthly water use time series $Q_b(m,y)$



$$a_0 = \frac{1}{12} \sum_{m=1}^{12} \left[\frac{1}{Y} \sum_{y=1}^Y Q_b(m,y) \right] \tag{5a}$$

where $Y = 16$ is the number of years,

$$a_k = \frac{1}{6} \sum_{m=1}^{12} \left[\frac{1}{Y} \sum_{y=1}^Y Q_b(m,y) \right] \cos\left(\frac{2\pi km}{12}\right) \tag{5b}$$

where $k = 1, 2, \dots, 6$,

$$b_k = \frac{1}{6} \sum_{m=1}^{12} \left[\frac{1}{Y} \sum_{y=1}^Y Q_b(m,y) \right] \sin\left(\frac{2\pi km}{12}\right) \tag{5c}$$

where $k = 1, 2, \dots, 6$ and $b_0 = 0$.

The Fourier coefficients are not necessarily all statistically significant but only for the appropriate significant test used. The seasonality of water use represented by $Q_b(y)$ is removed from the detrended water use time series $Q_b(m,y)$, resulting in deseasonalized water use series $Q_c(m,y)$, as shown in Eq. 6 (Mays and Tung 1992).

$$Q_c(m,y) = Q_b(m,y) - Q_b(m) \tag{6}$$

where the month $m = 1, 2, \dots, 12$, year $y = 1, 2, \dots, Y$ and $Q_b(m)$ is found using Eq. 4. To remove the seasonality found in detrended monthly water use, as shown in Fig. 3, the periodicity can be conveniently identified by detrending the monthly water use time series to a Fourier series using the average water use for each month of the detrended data. Here, the average water use $Q_b(m)$ can be computed by Eq. 3 for each month, using the detrended monthly time series $Q_b(m,y)$ obtained from Eq. 2. Table 5 shows the average water use $Q_b(m)$ in MCM.

Table 5 Average monthly water use $Q_b(m)$ in MCM

| Months | $Q_b(m,y)$ MCM | Months | $Q_b(m,y)$ MCM |
|------------|----------------|-------------|----------------|
| $Q_b(m=1)$ | -0.256 | $Q_b(m=7)$ | 0.5722656 |
| $Q_b(m=2)$ | -0.346938 | $Q_b(m=8)$ | 0.5804688 |
| $Q_b(m=3)$ | -0.200938 | $Q_b(m=9)$ | 0.4624219 |
| $Q_b(m=4)$ | -0.107563 | $Q_b(m=10)$ | 0.0156875 |
| $Q_b(m=5)$ | 0.08 | $Q_b(m=11)$ | -0.107394 |
| $Q_b(m=6)$ | 0.4891406 | $Q_b(m=12)$ | -0.164938 |

Table 6 Fourier coefficients

| a_k | Value | b_k | Value |
|-------|----------|-------|----------|
| a_0 | 0.084685 | b_0 | 0 |
| a_1 | -0.32183 | b_1 | -0.31676 |
| a_2 | 0.022804 | b_2 | 0.095057 |
| a_3 | 0.024779 | b_3 | 0.003316 |
| a_4 | 0.063289 | b_4 | 0.003062 |
| a_5 | -0.02762 | b_5 | -0.01071 |
| a_6 | -0.01166 | b_6 | -0.00037 |

The $Q_b(m)$ is computed using Eq. 3, and the Fourier coefficients are computed too but using Eqs. (5a-5b and 5c). The computed Fourier coefficients are shown in Table 6.

The Fourier coefficients in Table 6 and the average water use $Q_b(m)$ in Table 5 can be used by Eq. 4 to find the average monthly water use $Q_b(m)$ after being regenerated, as shown in Table 7.

Then, the deseasonalization monthly water use time series $Q_c(m,y)$ is obtained by Eq. 6, removing the seasonal trend. The monthly water use time series $Q_c(m,y)$ can be converted to $Q_c(t)$, where $t = 1, 2, \dots, 252$ for the deseasonalized water

Table 7 Model regenerated values $Q_b(m)$ (MCM)

| Months | $Q_b(m,y)$ | Months | $Q_b(m,y)$ |
|------------|------------|-------------|------------|
| $Q_b(m=1)$ | -0.41867 | $Q_b(m=7)$ | 0.412176 |
| $Q_b(m=2)$ | -0.51967 | $Q_b(m=8)$ | 0.408915 |
| $Q_b(m=3)$ | -0.19454 | $Q_b(m=9)$ | 0.468398 |
| $Q_b(m=4)$ | 0.049132 | $Q_b(m=10)$ | 0.181687 |
| $Q_b(m=5)$ | 0.249426 | $Q_b(m=11)$ | 0.062048 |
| $Q_b(m=6)$ | 0.4835 | $Q_b(m=12)$ | -0.16383 |

use time series for 1990–2010, as shown in Fig. 6. The proportion of dispersion is reduced for the monthly water use after removing the seasonality from the detrended monthly water use time series. Results using SPSS show that the deseasonalization monthly water use time series $Q_c(t)$ has a mean of -0.0002 and SD of 0.238, which is less than that of the detrended usage of 0.385.

Autoregressive filtering

The third stage in developing the cascade model is the autoregressive filtering analysis to identify the short-term memory components in $Q_c(t)$. The detrended and deseasonalized monthly water use time series $Q_c(m,y)$ now does not possess the monthly and seasonal trends. Still, this time series may have autocorrelation, like many hydrologic time series, so Eq. 7 can obtain $Q_c(t)$:

$$Q_c(t) = \sum_{i=1}^I \Phi_i Q_c(t-i) + Q_d(t) \tag{7}$$

where month $t=2, \dots, T$; $Q_c(t-i)$ is the detrended and deseasonalization of monthly water use time series lagged by i

months; I is the total number of lagged months, Φ_i is the autoregressive coefficient; and $Q_d(t)$ represents the residual water use time series after the autoregressive is removed. Within $Q_c(t)$, the autoregressive coefficients Φ_i and $Q_d(t)$ can be estimated using linear regression analysis in SPSS using Eq. 8:

$$Q_c(t) = \Phi_0 + \Phi_1 Q_c(t-1) \tag{8}$$

where month $t=2,3, \dots, 252$; $Q_c(t)=Q_c(m,y)$; and the residential $Q_d(t)$ represents the water use time series after autoregression is removed using Eq. 7. As a result, the autoregressive coefficients Φ_i are $\Phi_0 = -0.002$ and $\Phi_1 = 0.741$. The autocorrelation discovered in the time series measures the persistence of the observation, the existence of which can be identified by computing the autocorrelation coefficients of the different time lags. Thus, the autocorrelation in the deseasonalized water use time series can be used for only the lag - 1 autocorrelation. The residual $Q_d(t)$ values are found using Eq. 7. Note that the first value of $Q_d(1)$ equals zero, assuming that since t begins at $t=2$. In this autoregression of t ,

$$Q_d(t) = Q_c(t)(\text{measured}) - Q_c(t)(\text{modeled})$$

and given by

$$Q_c(t) = Q_c(1) + \dots + Q_c(252) \text{ for } t = 1.$$

Assuming no difference between measured and modeled, the first value $Q_d(1)$ equals zero, and the following equation represents $Q_d(t)$:

$$Q_d(t) = Q_c(t) - (-0.002 + 0.741 \times Q_c(t-1))$$

Fig. 6 Deseasonalization monthly water use time series $Q_c(t)$

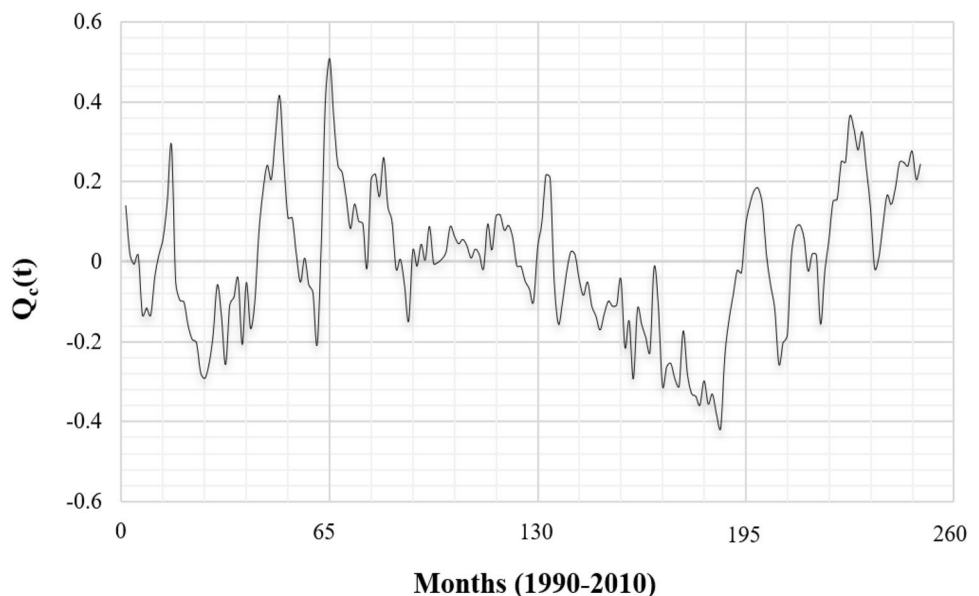
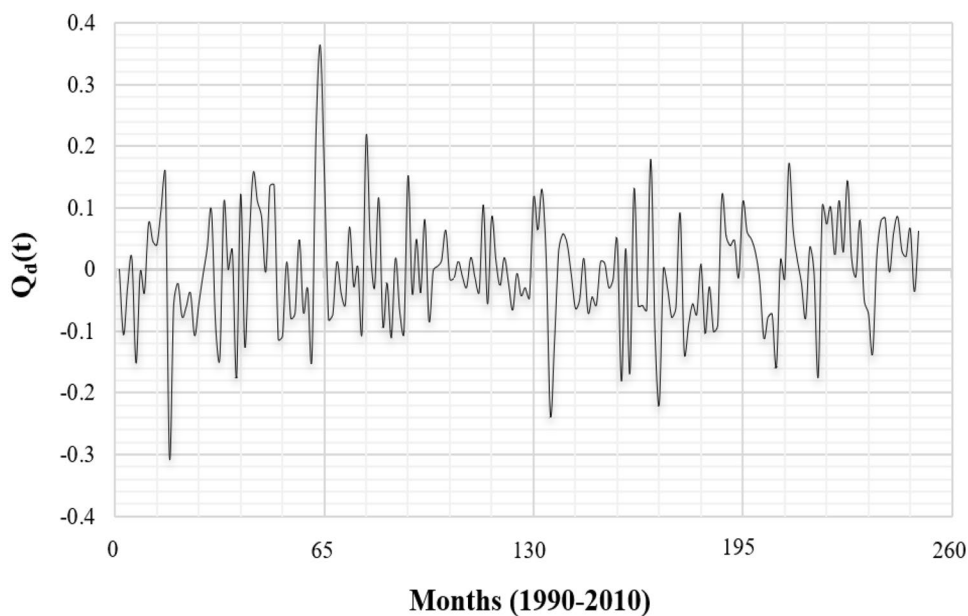


Fig. 7 Autoregressive monthly water use time series $Q_d(t)$



where $t = 2, 3, \dots, 252$.

Figure 7 shows the autoregressive monthly water use time series $Q_d(t)$ for 1990–2010, and the proportion of dispersion is reduced after removing the autocorrelation from the deseasonalized monthly water use time series $Q_c(m, y)$ using Eq. 7. Results using SPSS show that the autoregressive monthly water use time series $Q_d(t)$ has a mean of 1.49 and SD of 0.158, which is less than that of the deseasonalized value of 0.238; so, this stage reduced the dispersion.

Climatic regression

The final step in the cascade model development is to compute the monthly water use time series $Q_d(t)$, which accounts for two climatic parameters—monthly precipitation and monthly average temperature—for 1990–2010, as shown in Eq. 9:

$$Q_d(t) = \sum_{l=1}^L \beta_l x_l(t) + Q_e(t) \tag{9}$$

where $t = 1, 2, \dots, T$, x_l is the l th climatic factor, L is the total number of climatic factors, and $Q_e(t)$ represents the residual that balances the equation to a zero mean with constant variance. The model coefficients β_l in Eq. 9 can be estimated using linear regression analysis, historical data for the climatic variables, and the known values of the dependent variable $Q_d(t)$. From Eq. 9a, the regression equation is

$$Q_d(t) = \beta_0 + \beta_1 \times \text{monthly precipitation} + \beta_2 \times \text{max. monthly average temperature} + Q_e(t) \tag{9a}$$

where the precipitation is in mm and the temperature is in °C. From January to December 1990–2010, the monthly precipitation is zero in the summer months, and the highest monthly precipitation occurs in winter. The average maximum monthly temperature from June to October over the same period is higher than the other months because of summer, and the lowest temperatures are at the beginning and end of each year because of winter. Table 8 shows the model parameters found by the multi-linear regression analysis. Therefore, the two independent variables are expected to affect the monthly water use time series $Q_d(t)$, based on 16 years of historical data used to estimate the model parameters β_0 , β_1 , and β_2 .

The results using SPSS show the residual time series $Q_e(t)$ from climatic regression, which has a mean of 0.002, and SD of 0.02, less than that of the autoregressive monthly water use time series $Q_d(t)$ of 0.158. Thus, at this stage, the rates of dispersion are again reduced, as shown in Fig. 8.

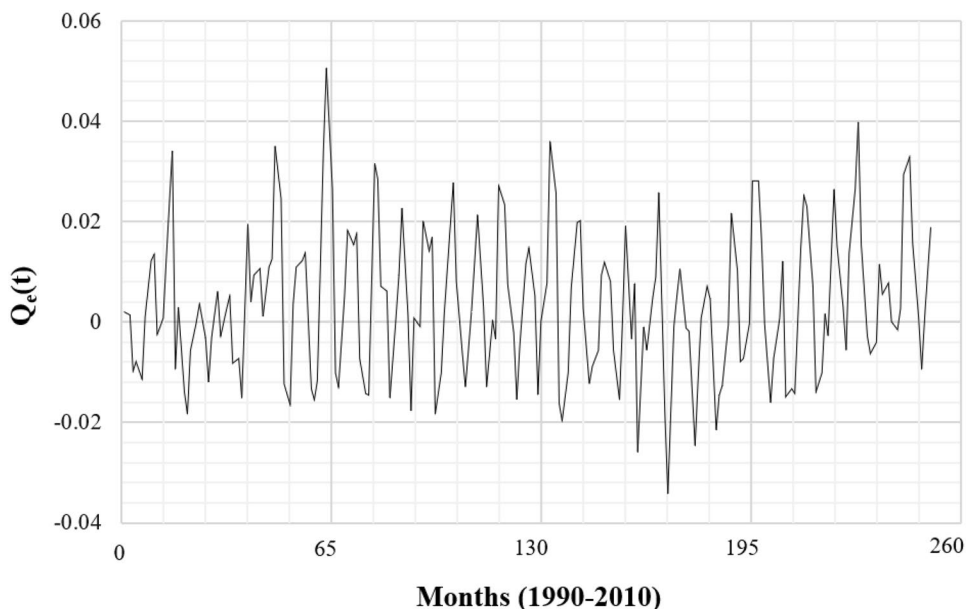
Application for forecasting the future municipal water demand

To forecast the municipal water demand by transforming historical monthly water use, the cascade model is developed with its estimated coefficients. Then, future municipal water

Table 8 Regression coefficients

| Coefficients | Value |
|--------------|--------|
| β_0 | -0.054 |
| β_1 | 0.0005 |
| β_2 | 0.0015 |

Fig. 8 A pure random error series $Q_e(t)$



demand can be predicted by the developed cascade model using Eq. 11:

$$Q_a(t) = Q_a(m, y) = Q_a(y) + Q_b(m) + Q_c(t) + Q_d(t) \quad (11)$$

where the predicted values of each term can be calculated using Eqs. 1, 4, 8, and 9a.

The coefficients η , a_k , b_k , ϕ , and β can be estimated using regression analysis. Hence, to forecast values of $Q_a(y)$, the future socioeconomic factors related to population growth in thousands, annual family income (JD), and annual precipitation (mm) must be identified. However, the seasonality component $Q_b(m)$ depends only on the month being considered. To calculate the future value of deseasonalized water use time series, $Q_c(t)$ depends on the last I in the historical data time series $\{Q_c(t), T - I \leq t \leq T\}$, which $Q_c(t-i)$ is the detrended and deseasonalized monthly water demand series lagged by i months; I is the maximum number of lags ϕ 's which are the unknown autoregressive model parameters; and $Q_d(t)$ is the residual representing the water use time series after autocorrelation within $Q_c(t)$ has been removed that are needed to perform the recursive calculation.

Finally, to find $Q_d(t)$, forecasting the climatic variables is necessary. The future total water use is then the sum of all four components. Before predicting future water demand, two analysis steps are performed. First, the accuracy of the model for 1990–2010 is calculated. Second, the model is verified for 2011–2020, and then the water used for 2021–2030 can be forecasted.

Accuracy of the model for 1990–2010

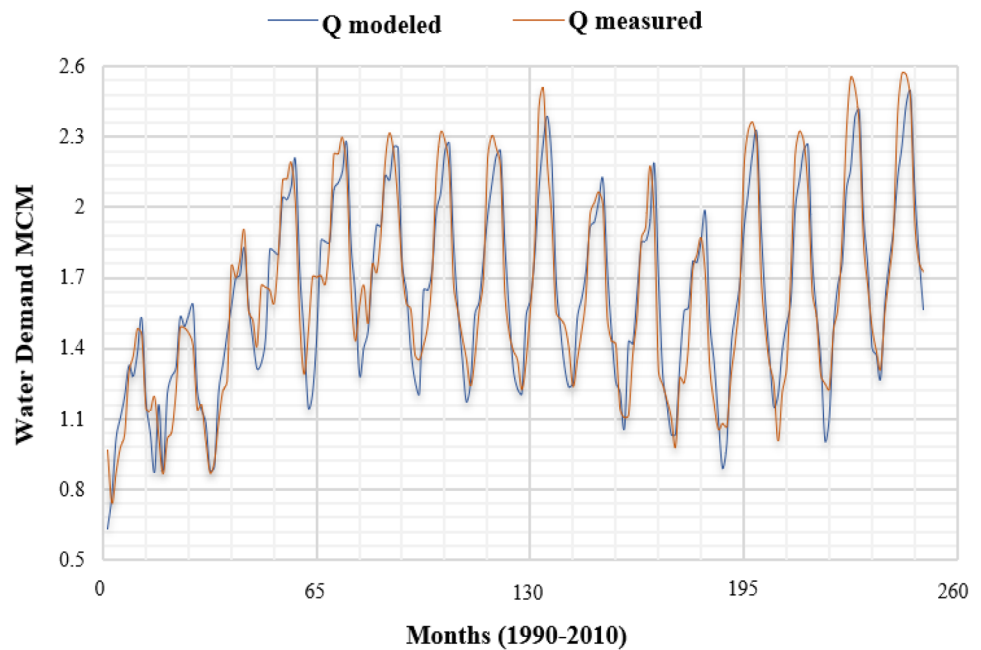
After developing the cascade model from historical data using time series analysis in four development stages, the estimated values of η , a_k , b_k , Φ , and β from the regression analysis were employed using historical data for 1990–2010. The data included population growth in thousands, annual income, annual precipitation, monthly precipitation, and monthly temperature. Therefore, the historical data related to total municipal monthly water use time series $Q_{measured}$ (MCM) can be compared to the estimated total municipal monthly water use $Q_{modeled}$ (MCM).

In this regard, the cascade model is tested by two approaches: determining the accuracy of the model using historical data for 1990–2010 and validating the cascade model for 2011–2020. The available historical data of socioeconomic factors for 2011–2020 were used to measure the model's validity using the estimated values of η , a_k , b_k , Φ , and β from the regression analysis in Eq. 11.

In the measured vs. modeled comparison for 1990–2010, the differences between $Q_{measured}$ and $Q_{modeled}$ varied as large, medium, and very small. This was due to other socioeconomic factors that were not adopted in the development of the cascade model. The results of the development cascade model stages can give a sort of reassurance for the forecast of monthly water demand. Note that, to estimate the total municipal monthly water use $Q_{modeled}$, the components for the development of cascade model stages Q_a , Q_b , Q_c , and Q_d need to be determined.

Figure 9 shows the differences between the total demand $Q_{measured}$ and $Q_{modeled}$. The water demand in the Al-Balqa governorate for 1990–2010 is also shown based on the time series model in Eq. 11. Finally, the method of

Fig. 9 Water demand modeled vs. measured for 1990–2010



verification of the forecasted model can indicate compatibility with the historical water demand during 1990–2010.

Clearly, the levels of water demand increased in some months and decreased in other months. The study found the arithmetic average yearly water demand $Q_{modeled}$ of 1.80, which was less than the arithmetic average $Q_{measured}$ of 2.06. In addition, the maximum predicted water consumed was 2.25, compared to the maximum measured value of 3.03. The minimum predicted water quantity consumed was 1.17, compared to a measured 1.41. The largest difference between $Q_{modeled}$ and $Q_{measured}$ monthly values during 2006–2010 was in August 2010 by 0.28. Moreover, the smallest difference occurred in May 2009 by 0.01. The study revealed that the lowest water usage occurred from January to March 2007, and the highest water usage in the province was from May to October 2010.

Indeed, harmony exists between the $Q_{measured}$ and of $Q_{modeled}$ for 1990–2010. At this stage of analysis, specific measures of model performance, as statistical indicators, were employed to assess the model quantitatively:

- Variance of the residual error.
- SD of residual error.
- Mean of absolute residual error.
- Absolute differences in the means.
- Root mean squared residual error.

Table 9 shows the statistical indicators as related to the absolute difference that validate the cascade model in the

Table 9 Statistical indicators of the residual error

| Statistics | Absolute differences |
|----------------------|----------------------|
| Mean | 0.082039472 |
| Std. error of mean | 0.004590295 |
| Std. deviation | 0.063604992 |
| Variance | 0.004045595 |
| Root mean of squared | 0.10371 |

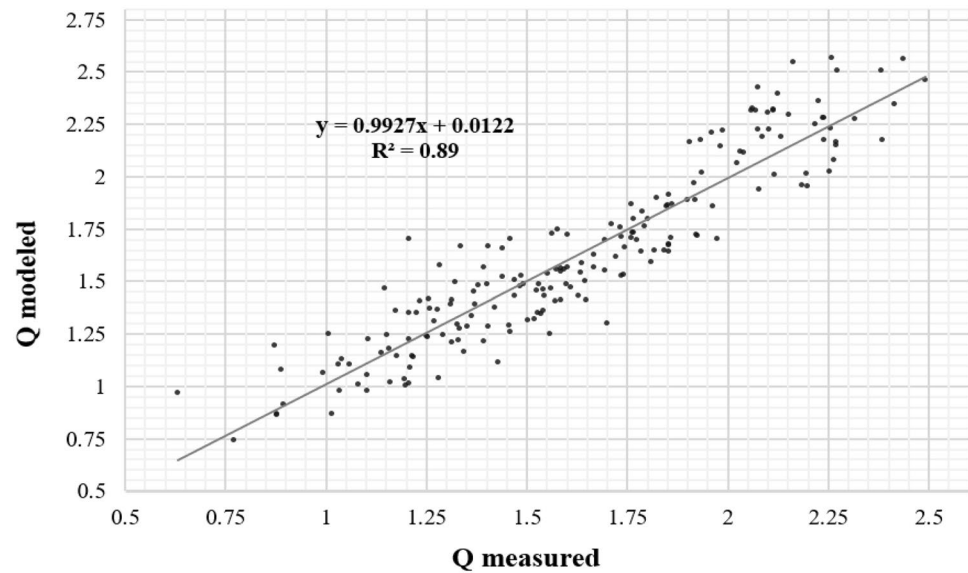
forecast of monthly water demand. Of note, to estimate the total municipal monthly water use $Q_{modeled}$, the components for the development of cascade model stages, Q_a , Q_b , Q_c , and Q_d , need to be determined first.

Figure 10 illustrates the linear regression between $Q_{modeled}$ and $Q_{measured}$. The plot of this relationship indicates the differences are small. Figure 10 shows the R^2 value (also known as the coefficient of determination or the coefficient of multiple determination for multiple regression) for the WDM of $Q_{measured}$ vs. $Q_{modeled}$.

The R^2 value is a statistical measure of how well the data fit the regression model, representing the proportion of the variance for a dependent variable that is explained by an independent variable or variables in a regression model (Cameron & Windmeijer 1997). The variability of the response data around the mean is explained by R^2 , which is between 0 and 1. A low R^2 generally indicates a poor predictive model.

Although the statistical measure provides some useful insights regarding the regression model, the user should

Fig. 10 Water demand modeled vs. measured for 1990–2010



not rely only on the measure in the assessment of a statistical model (Cameron & Windmeijer 1997). For instance, Fig. 10 does not disclose information about the causal relationship between the independent and dependent variables. In Fig. 10, R^2 equals 0.89, which, based on statistical measures, indicates the model is acceptable.

Model validity for the forecasted water demand period of 2011–2020

In the model validation stage, three steps were executed to assess the developed cascading model's application in practices in Jordan to predict water needs.

Using the standard error of estimates

After the cascade model was applied to forecast water demand for 2011–2020, the researcher collected real data from the authority of water in Jordan. The collected $Q_{measured}$ was compared with $Q_{modeled}$ data. The calculation of the standard error of estimates (Se) showed that the differences between the two datasets were very small, indicating the developed model is accurate to be used for forecasts. However, the differences between $Q_{measured}$ and $Q_{modeled}$ were still present since some variables were not considered during the model development.

The variable Se measures the variation of an observation made around the computed regression line. Simply, it checks the accuracy of predictions with the regression line (Leith 1973). Like SD, which measures the variation in the set of data from its mean, Se also measures the variation in the actual values $y_{measured}$ from the predicted values $y_{modeled}$ on the regression line for 2011–2020. It is computed as

an SD, and here the deviations are the vertical distance of every point from the line of the average relationship.

Using Eq. 13 to calculate Se for both $Q_{measured}$, and $Q_{modeled}$ is necessary to verify the data are acceptable and validate the model for predicting water demand. The deviation of each point from the regression line is expressed as $y_a - y_e$ (Leith 1973). Once these values are calculated, the standard error of estimates can be calculated using Eq. 13:

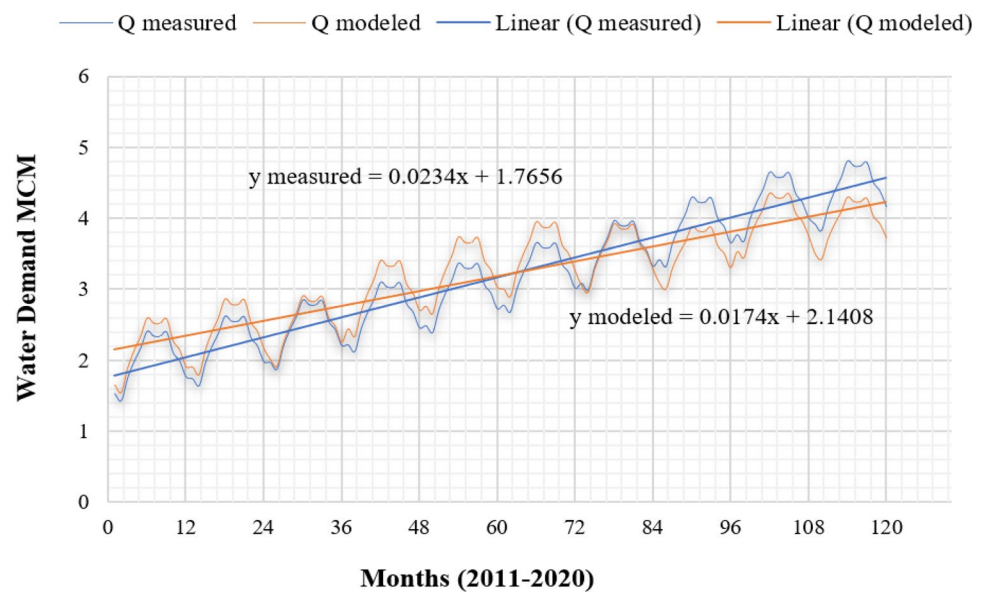
$$Se = \sqrt{\frac{\sum (y_a - y_e)^2}{n - 2}} \quad (13)$$

where y_a is the actual n th value, y_e is the estimated n th value, and n is the number of observations. To find y_e for $Q_{measured}$ and $Q_{modeled}$, the results obtained from the trend line equation in Fig. 11 were related to the estimate values y_e , which then were used in Eq. 13. To find Se , $Q_{measured}$, and $Q_{modeled}$ were plotted, as shown in Fig. 11. Then, the trend line was plotted, and $Q_{measured}$, and $Q_{modeled}$ were reused in the related formula given in Fig. 11.

The smaller Se is evident when the point is closer to the regression line, indicating a better estimate based on the equation of the line (Leith 1973). If $Se = 0$, then no variation from the computed line is present, and the correlation will be perfect. The calculated Se for $Q_{measured}$ is about 0.302, while Se for $Q_{modeled}$ is 0.343. Clearly, both values are close together, which indicates that the statistical analysis was acceptable. As mentioned earlier, the small differences in these values were due to circumstances that were not considered. In addition, these factors were not considered when developing the cascade model but then used as input data to predict the future water demand.

Thus, the Se measures the accuracy of the estimated values, i.e., the goodness and representativeness of the

Fig. 11 Q measured vs. Q modeled of water demand for 2011–2020



regression line, and represents a description of the average relationship between the two series. The Se value indicates how large the prediction errors (residuals) are for the dataset in the same units as Y (Leith 1973). For an accurate forecast, Se needs to be a small value.

To calculate Se , the trend line of Q measured, and Q modeled was first determined, and then the monthly data were input into the equation to obtain the error for each observed data point. The results show no large difference between Q measured and Q modeled, which indicates the slopes are close together and systematic. In addition, no large difference was present in the Se values between the two datasets. As a result, the observed data are similar, and the model is, thus, valid for forecasting water demand.

Sensitivity analysis to forecast water demand with varying social and climatic factors

Sensitivity analysis is a measure of the stability of a system (Al-Sakkaf et al. 2021). In simple terms, the input parameters are adjusted by a specific value, and the system's overall condition is observed (Al-Sakkaf et al. 2021). The following scenarios illustrate the results of the sensitivity analysis. As shown, the overall condition is not affected by significant changes. For instance, the largest difference appears in the first case for increased population, indicating this factor is significant in the model development. On the other hand, the smallest change is related to precipitation. However, despite these differences, the system's stability is not affected drastically in all the scenarios.

The social and climatic factors which affect water use can be increased or decreased while keeping other factors fixed. Thus, the effects of social and climatic factors can be studied

in relation to annual population growth, annual precipitation, monthly precipitation, and monthly temperature. Then, any changes in the predicted water use can be measured.

Scenario 1: Changing the annual population growth

In Scenario 1, the future water use Q total forecast in Al-Balqa governorate for 2011–2020 is predicted after the rate of population growth changes from 2.9% to three rates of 3.1%, 3.3%, and 3.5%. This total predicted future water can be summarized by the mean values of the Q total forecast. When the annual population growth rate increases to 3.1%, the mean value of consumption water is 3.49 MCM. However, at 3.5%, the mean consumption reaches 4.06 MCM. Therefore, the increase in annual population growth is a key factor for the increasing water demand in the future.

Scenario 2: Changing yearly and monthly precipitations

In Scenario 2, the future water use Q total forecast in Al-Balqa governorate for 2011–2020 is predicted after the yearly and monthly precipitations are increased and decreased by 10%, 20%, and 30%. When the annual precipitation was decreased, the mean total predicted future water use Q total forecast increased. It also showed a decrease in the mean values of total predicted future water use Q total forecast when the annual precipitation was increased. When the precipitation increases by 10% and 20%, the mean consumptions are 2.997 and 2.976 MCM, respectively. On the other hand, when the yearly and monthly precipitations decrease by 10% and 30%, the mean water consumption increases to 3.018 and 3.04 MCM, respectively. Therefore, an increase in yearly and monthly precipitation decreases

the mean water consumption use and vice versa, an inverse relationship, because of water harvesting in the winter.

Scenario 3: Changing in monthly temperature

Scenario 3 predicts water use Q total forecast in Al-Balqa governorate for 2011–2020 based on changes in monthly temperature by $\pm 10\%$, 20% , and 30% . The mean total predicted water use Q total forecast increases when the monthly average temperature increases. In addition, the mean consumption decreases when the monthly average temperature decrease. Specifically, when the monthly average temperature increases by 10% , the mean consumption increases to 3.014 MCM, reaching 3.022 MCM when the temperature increase is 30% . Similarly, when the temperature decreases by 10% , the mean water consumption decreases to 3.007 MCM, reaching 2.999 MCM when the temperature change is -30% . Therefore, increasing of monthly average temperature raises the mean value of water consumption use (and vice versa) because of the summer season.

Using expert interviews

Eight experts from the MWI with wide ranges of experience in the field were interviewed. The interviewees were chosen based on their expertise and specializations in the field of water demand. The interviews were semi-structured and based on a list of questions. The information that was obtained was used to validate the model by interpreting the results from applying the model. Three questions were posed to the eight experts:

1. What causes the difference between the Q modeled and Q measured?
2. How do you interpret the results?
3. What recommendations do you propose to cope with the increased demand?

In line with the current COVID-19 restrictions in Jordan, the interviews were conducted over Skype and ZOOM. The experts' profiles are given in Table 10.

As a result, all the information obtained from the interviewees was transcribed, analyzing each line through micro-analysis. This approach provides insights into the most valuable suggestions to be used when validating the forecasting model. The experts were asked to explain the statistical measure of the R^2 , which is equal to 0.92, as shown in Fig. 12. They stressed that this statistical measure in a regression model determines the proportion of variance in the dependent variable that can be explained by the independent variable. They all agreed that $R^2 = 0.92$ is a good indication of the relationship between the independent and

Table 10 Experts' information profiles

| Expert code | Job title | Experience | Interview duration |
|-------------|-----------|------------|--------------------|
| E1 | Engineer | 16 | 55 min |
| E2 | Engineer | 17 | 45 min |
| E3 | Director | 18 | 30 min |
| E4 | Director | 20 | 60 min |
| E5 | Director | 23 | 50 min |
| E6 | Engineer | 19 | 40 min |
| E7 | Director | 21 | 35 min |
| E8 | Director | 19 | 45 min |

dependent variables, particularly for predictive models. Therefore, they deemed the proposed model is very good in water demand forecasting. However, a few of the experts stressed that the model needs to be modified to address the uncertainties and consider the global developmental circumstances in addition to the technological development in Jordan.

In this phase of research, the researcher interviewed experts in the field working in the water sector. To this end, the results of the model were presented to the experts for discussion to determine the causes of the differences between the Q measured and Q modeled. All experts agreed that the most significant factor related to the increase in population growth due to the instability in the region, especially in the last few years.

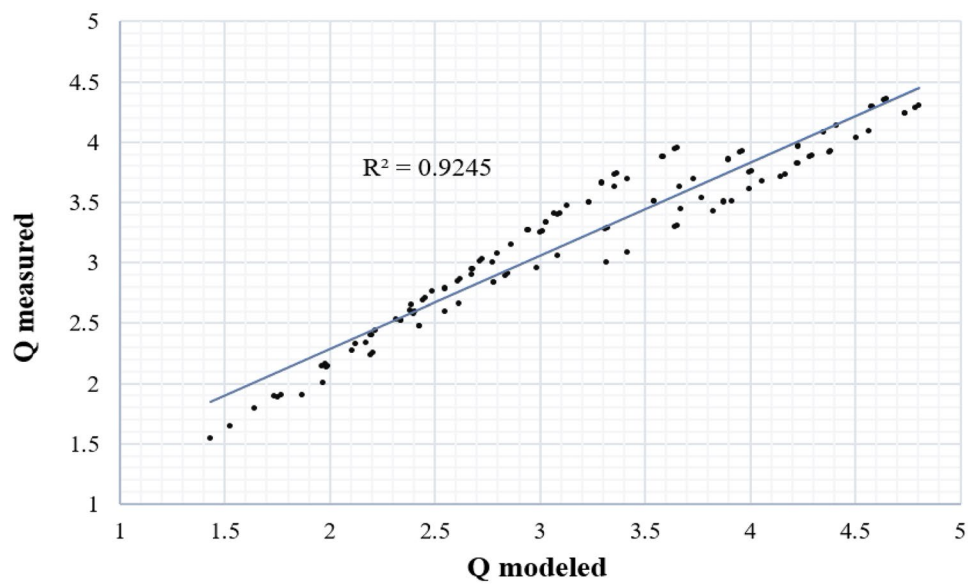
Most agreed that the demand was more than measured because, in the last seven years, most citizens used water from private suppliers, which was not included in the model. Others added that development in the human lifestyle affects the use of water and increases its demand.

Moreover, in recent years, the demand for water has changed its pattern. The interviewees agreed that the monthly water consumption from June to September for each year could be supplied by the private sectors, which can be considered a non-water demand. This means that private companies supply safe drinking water through the tap for washing and cooking. This activity indicates the need for more governmental measures to cope with the increased water demand to provide all citizens with access to safe drinking water.

Furthermore, most demand for water is during the summer, from June to September, and then the water usage dramatically drops to reach a minimum by the end of December. Then, after the first few months of the year, the demand increases linearly. This phenomenon is due to the hot and cold seasons affecting demanding water for municipal uses, such as cooking, drinking, and washing.

In addition, from the beginning of 2017, the Q measured was lower than Q modeled because of government measures. Also, with the emergence of COVID-19 at the beginning of

Fig. 12 Plotting trend line of regression for $Q_{measured}$ vs. $Q_{modeled}$ for 2011–2020



2020, the demand for drinking water decreased as the death in Jordan increased. Furthermore, human activities declined as the country’s lockdown was extended by four months. Still, various human activities, such as working outside the home, were still on hold until late 2021, keeping the demand for water low. The records in Jordan indicate that the water demand in that period was low in contrast with the same period of the year before. As a result, the experts claimed that these variables did not consider the sensitivity and uncertainty of population growth due to the instability of the region from violence and the influx of refugees. Therefore, the expert interviews provided valuable insights into the difference between the $Q_{measured}$ and $Q_{modeled}$.

Future water demand forecasting for 2021–2030

To forecast values for $Q_d(y)$, the future socioeconomic factors related to population growth, annual family income, and annual precipitation should be determined. However, the seasonality component $Q_b(m)$ depends only on the month being considered, so the values shown in Table 9 are taken as future values of $Q_b(m)$ for the months of January to December from 2021–2030. To calculate the future value of deseasonalized water, the time series $Q_c(t)$, which depends on the last I historical data time series $\{Q_c(t), T - I \leq t \leq T\}$, is needed. The last I in the historical data is December 2010, and then the value of $Q_c(252)$ is calculated using Eq. 8 to find the future $Q_c(t)$ for 2011–2020.

Finally, to find $Q_d(t)$, forecasts of the climatic variables are necessary. The future municipal water demand can be predicted by the developed cascade model using Eq. 11 for 2011–2020. Forecasting the socioeconomic factors related to population, annual family income, annual precipitation, monthly precipitation, and monthly temperature is necessary

to compute the expected water use demand. The average rate of population growth k can be computed from the historical data in Table 3. For 1990–2010, $k = 2.9\%$, which was used in Eq. 12 to predict the population for 2021–2030.

$$Pop(t) = Pop_0 \times (1 + k)^n \tag{12}$$

where n number of years, $Pop(t)$ is the population at time t , and Pop_0 is the starting population. Results are shown in Table 11.

The other factor that has to be predicted is annual income, which can be computed from the historical data for 1990–2010 in Table 2. This factor can be predicted through a linearly increasing rate, as shown in Table 11. Finally, the annual precipitation must be predicted, which can be taken as the average value related to annual precipitation from the historical data in Table 2 for 1990–2010. This value of 459.33 mm is assumed as the predicted future value for

Table 11 Population growth in thousands, annual family income (JD), annual precipitation (mm) for 2021–2030

| Year | Population (thousand) | Income (JD) | Precipitation (mm) |
|------|-----------------------|-------------|--------------------|
| 2021 | 572.7414 | 1450.61 | 459.33 |
| 2022 | 589.3509006 | 1482.02 | 459.33 |
| 2023 | 606.4420767 | 1513.43 | 459.33 |
| 2024 | 624.0288969 | 1544.84 | 459.33 |
| 2025 | 642.125735 | 1576.25 | 459.33 |
| 2026 | 660.7473813 | 1607.66 | 459.33 |
| 2027 | 679.9090553 | 1639.07 | 459.33 |
| 2028 | 699.6264179 | 1670.48 | 459.33 |
| 2029 | 719.915584 | 1701.89 | 459.33 |
| 2030 | 740.793136 | 1733.3 | 459.33 |

annual precipitation to find $Q_a(y)$. In summary, Table 11 shows the predicted values for socioeconomic factors and the forecasted values of $Q_a(y)$.

Other components that are predicted include the seasonal component $Q_b(m)$, as shown in Table 7, the deseasonalized water use time series $Q_c(t)$, and $Q_d(t)$. To predict $Q_d(t)$, the climatic variables need to be forecasted. The average values are the monthly precipitation and monthly temperature from the historical data for 1990–2020, which are assumed predicted future values. Table 12 shows the average monthly precipitation and monthly temperature, in which the maximum monthly average precipitation occurred in February and the minimums were in August and September. Furthermore, the maximum monthly average temperature occurred

Table 12 Average precipitation and temperature (Meteorological Department 2022)

| Month | Avg. precipitation (mm) | Avg. temperature (°C) |
|-------|-------------------------|-----------------------|
| 1 | 91.87 | 17.88 |
| 2 | 105.37 | 16.28 |
| 3 | 101.82 | 16.46 |
| 4 | 64.60 | 20.42 |
| 5 | 21.71 | 25.56 |
| 6 | 3.41 | 30.29 |
| 7 | 0.2 | 33.02 |
| 8 | 0 | 34.44 |
| 9 | 0 | 34.39 |
| 10 | 0.61 | 32.39 |
| 11 | 20.7 | 28.9 |
| 12 | 49.04 | 22.35 |

in August, and the minimum was in February (Metrological Department, 2022).

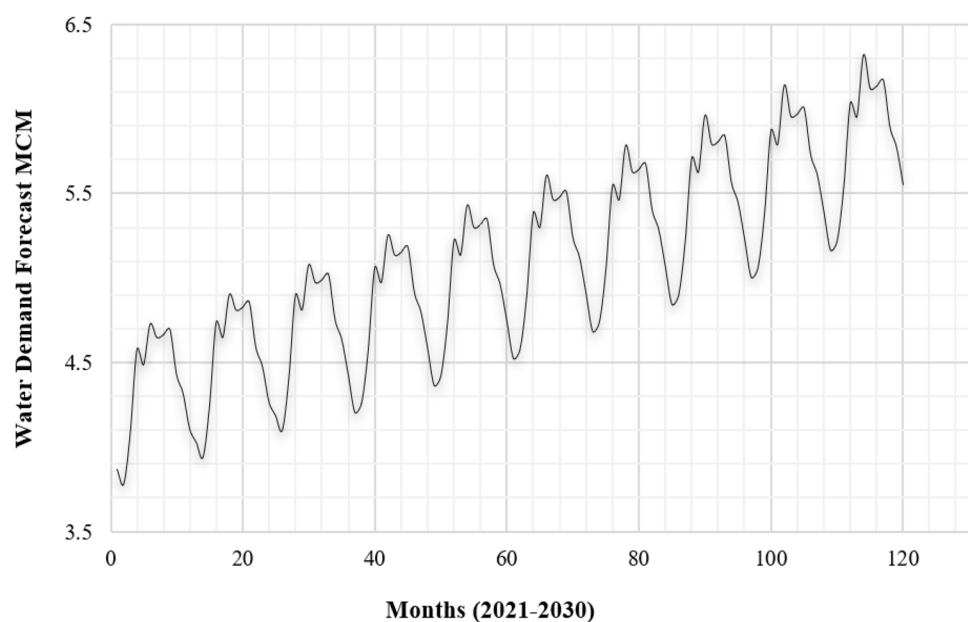
Finally, the future total monthly water use Q total forecast in Al-Balqa governorate for 2021–2030 can be predicted as the sum of all four components. Figure 13 shows the Q modeled forecast for this case. The R^2 value is 0.88 of Q modeled and Q measured for 2011–2020. (In some cases, a good model may show a small R_2 value.) With the effects of the climatic factors and the population increase, Q modeled forecast is expected to reach 69.88 MCM in 2030. Also, the municipal water demand reaches its highest value of 6.32 in June 2030. On the other hand, the lowest value of the Q modeled forecast is 3.78 in February 2021. Therefore, these results call for the development of specialized programs and methods to reduce water demand in the Al-Balqa governorate, owing to the increase of population to 740,790 persons in 2030.

Discussion and conclusions

Based on the results obtained from the cascade model and interviews, Jordan still faces significant issues regarding the balance between water demand and supply. In addition, Jordan is suffering from bad management practices in developing such measures to cope with the development because of the challenges facing the water sector.

As a result, the government of Jordan needs to develop a national policy for water. This policy is essential to cope with the increased water demand and meet service requirements. The policy should also be carried out to enhance water supply management, which will improve water demand response, water transfer allocations, and the water

Fig. 13 Forecasted water demand for 2021–2030



deficit. In addition, methods are required to optimize water consumption, availability, suitability, sustainability, and uses of available renewable freshwater resources (Hadadin 2010; MPIC 2017; MWI 2011).

The findings indicate a need to create a new motion for the sector to be better prepared and more efficient for effective water demand management. In addition, a plan to bridge the gap between water demand and supply is needed. Moreover, a major problem for the Al-Balqa governorate is the scarcity of water under difficult water circumstances, owing to the change in the rainfall and its yearly fluctuation. As a result, an increase in citizen awareness is necessary to follow practices, such as conserving water in various fields, harvesting rainwater, and reusing treated wastewater.

The main conclusions from the current research are as follows:

- a) To forecast monthly municipal water use in Al-Balqa governorate for 2021–2030, historical data for 1990–2010 was used, where monthly municipal water use is the dependent variable, and socioeconomic factors and climatic factors are independent variables. The correlation coefficients between water demand and these factors indicate that the primary factors affecting water demand forecasting are population and the improved level of lifestyle.
- b) Before forecasting the monthly municipal water use in the Al-Balqa governorate for 2021–2030, two analysis steps were executed. First, the accuracy of the model was calculated for 1990–2010. Second, the model was validated for 2011–2020. The results of these analysis steps $Q_{measured}$ and $Q_{modeled}$ can be compared, in which the latter is estimated using time series analysis. The results show a difference between the $Q_{measured}$ and $Q_{modeled}$, varying between large, medium, and very small. These two steps showed that the cascade model could forecast monthly water use.
- c) The differences between $Q_{measured}$ and $Q_{modeled}$ were due to other socioeconomic factors that were not adopted in the development of cascade model stages.
- d) A significant increase in water demand was predicted for 2021–2030, which will reach 69.88 MCM in 2030. This increase in water demand is due to the population increase in the years of study. This rapid population growth comes from the natural increase of population, an increase in births, the improvement of health services, the reduction of death numbers, and demographic factors (i.e., refugees).

Recommendations and future pathways

The research findings and expert interviews yielded recommendations to manage water demand and limit its use. In addition, the experts suggested that these practices need to be embedded in the policy and strategy development of the government and MWI. Moreover, this method of water demand forecasting using time series analysis is crucial to predicting water needs. It is considered a proactive approach for predicting water needs, which can enable the decision-makers of water supply to optimize water availability in the future and bridge the gap between supply and demand.

The experts agreed that effective water demand forecasting is the only way to secure the availability of water. In addition, the policymakers in the country can plan for future needs and eliminate the water shortage. Jordan can reach this goal by adopting a set of measures and practices to achieve sustainable development without compromising the future and current generations' needs.

The experts proposed the following practices:

- a) Observations of the water networks and distribution, with the regular maintenance of such networks, and detection of illegal water use and leakages to save water, limit the lost water, and punish violators.
- b) Establishment of citizen awareness through advertising campaigns by encouraging modern management tools, using technological devices to limit water consumption, and using the water harvest method to gather water.
- c) Continuation of the use of ascending slides of water tariffs to limit water depletion for all the municipal, industrial, and agricultural sectors.
- d) Participation by public and private sectors and concerned parties in limiting the depletion of water resources and increasing the efficiency of use, in addition to using the best management means to limit the illegal use of water.
- e) Various programs to control the birth rate and limit the natural increase of the population, especially since Jordan suffers from sudden emigrations due to the regional situations in the middle east.
- f) Realization of equitable access to safe drinking water by reducing pollution, eliminating dumping, minimizing the release of polluted water, and increasing water-use efficiency across all sectors.
- g) Implementation of management practices at all levels through capacity-building support in water savings, including water harvesting, desalination, water efficiency, wastewater treatment, and recycling.
- h) Strengthening the participation of local communities in improving the water demand management programs.

Correlation of the study's outcomes with SDG

The correlation between the current study and the SDGs is imperative to understand. SDG6 “water” was established to achieve the availability of water for all using sustainable management practices. These practices are essential to unlock economic growth and provide significant leverage for water resources and access to safe drinking water (UN, 2015).

The outcome of the present study conducted on Jordan can be used as a proactive approach to confront policy-makers who plan the management of future water demand. Therefore, forecasting the water demand is needed to address the development of Jordan's activities and rapid population increase, with the current water supply not expected to meet this demand. Furthermore, water demand forecasting for municipal purposes is crucial to the efficient use of water, reallocation among uses and sectors, and establishment of good water governance.

Since the primary target of SDG6 is to provide all people access to safe drinking water, forecasting water usage leads decision-makers to set alternative methods. Moreover, forecasting the demand and understanding future needs can reduce the imbalance between demand and supply in Jordan. To this end, using historical data to show the extent of usage of water is crucial to estimate the available water in the future and establish ways to influence water usage. The probable results can accurately estimate the future demand for water consumption.

People's participation for further use

People participation is critical from different perspectives. In fact, effective, regular communication between science and people is required for the understanding of problems raised. As a result, the experts provided immediate solutions and real possibilities for each potential consequence to act with rational decisions. Participation of the people is important to continue in current research, such that they can benefit from the findings and decide which actions should be performed.

In addition, the interviewed experts interpreted and discussed the findings and confirmed the model is valid for application. Therefore, their participation is valuable in using the model and developing it for other areas in the country. Furthermore, they can help address the critical problems that may occur in future water demand by recommending management practices for water demand to reduce water losses and establish the availability of water for current and future generations.

Science communication

A scientific paper is a mode of scientific communication that makes science accessible to various audiences. Science communication is a practicing term for informing and inspiring the public with scientific knowledge. According to Matta (2020), scientific communication is vital to communicate with society beyond barriers. It is critical to solving the world's most urgent issues. The impact of science communication interplays government–expert–public or society that can help promote positive behavioral change (Matta 2020).

Indeed, the public wants to understand science and know how a new finding may impact life. In this regard, this paper can provide great opportunities for the public to use the scientific findings and obtain new solutions to their life issues. Moreover, communication with the community regarding societal problems requires input from general citizens. This can motivate researchers to search for solutions to benefit society.

In fact, the availability of water is one of the most critical issues across the world. It requires clear and effective communication to increase scientific understanding of how to deal with this concern that affects the development of the country. This issue needs to be studied further, such that water is available to current and future generations without compromising their needs.

Science requires effective communication, and this paper conducted an empirical study to forecast the future water need. In addition, the current research employed the data collected from authorities in Jordan and society to develop a cascade model for forecasting water demand in Jordan. This work is essential to recommend such measures observed by the public to find new solutions to the issues facing Jordan. Confidence can be built between researchers and the public, such that the information is used to overcome the gap between water demand and supply. Those interested in the current research can apply the results in practice. Therefore, the current study is a paper-based solution as a proactive approach to future problems. It can educate society from various disciplines and agencies, like industries, academia, research institutes, policymakers, and the public, about good decision-making toward water conservation and availability, solving the complex problem of the future water need.

This paper tries to communicate with society and researchers in a simplified way through flowcharts, figures, and a description of the developed model. The paper shows the expected population, income, precipitation, temperature, and finally, the demand for water to be used for creating an effective communication plan with society. Lastly, the current study can be communicated by publishing the findings and sharing them on digital platforms, filling the gap in previous research on water demand forecasting.

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Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- Abdallah L, Abdel F (2010) Trend in the growth of water demand management facilities in Jordan's tourism sector. *J Soc Sci* 3(3):2
- Abdel Khaleq R (2008) Water demand management in Jordan, report: water efficiency and public information for action. Ministry of Water and Irrigation
- Ajbar AH, Ali EM (2015) Prediction of municipal water production in touristic Mecca City in Saudi Arabia using neural networks. *J King Saud Univ Eng Sci* 27:83–91
- Al-Dorgham S, Mai A (2008) Adjusting the irrigation water demand projection module to be viable in the Jordan valley. Civil Engineering Department—Water Resources and Environmental Engineering, Jordan University of Science and Technology
- Alissa S (2007) Rethinking economic reform in Jordan: confronting socioeconomic realities. Carnegie Middle East Centre
- Almutaz I, Ajbar A, Khalid Y, Ali E (2012) A probabilistic forecast of water demand for a tourist and desalination dependent city: case of Mecca, Saudi Arabia. *Desalination* 294:53–59
- Al-Sakkaf A, Bagchi A, Zayed T, Mahmoud S (2021) Sustainability assessment model for heritage buildings. *Smart Sustain Built Environ*
- Balling R, Gober P (2006) Climate variability and residential water use in the city of Phoenix, Arizona. *J Appl Meteorol Climatol* 46:2
- Bond NR, Burrows RM, Kennard MJ, Bunn SE (2019) Water scarcity as a driver of multiple stressor effects. In: Sabater S, Elozegi A, Ludwig R (eds) *Multiple stressors in river ecosystems*. Elsevier, Amsterdam, pp 111–129
- Cameron AC, Windmeijer FA (1997) An R-squared measure of goodness of fit for some common nonlinear regression models. *J Econ* 77(2):329–342
- Chaplin MF (2001) Water: its importance to life. *Biochem Mol Biol Educ* 29(2):54–59. [https://doi.org/10.1016/S1470-8175\(01\)00017-0](https://doi.org/10.1016/S1470-8175(01)00017-0)
- Department of Meteorological. (2011) Yearly report
- Hadadin N, Qaqish M, Akawwi E, Bdour A (2010) Water shortage in Jordan—sustainable solutions. *Desalination* 250(1):197
- Jaber J, Mohsen M (2020) Evaluation of non-conventional water resources supply in Jordan. *Desalination* 136:83–92
- Lawgali FF (2008) Forecasting water demand for agricultural, industrial and domestic use in Libya. *Int Rev Bus Res* 4(5):231–248
- Leith CE (1973) The standard error of time-average estimates of climatic means. *J Appl Meteorol* 12(6):1066–1069
- Matta G (2020) Science communication as a preventative tool in the COVID19 pandemic. *Human Soc Sci Commun* 7(1):1–14
- Matta G, Kumar P, Uniyal DP, Joshi DU (2022) Communicating water, sanitation, and hygiene under sustainable development goals 3, 4, and 6 as the panacea for epidemics and pandemics referencing the succession of COVID-19 surges. *ACS EST Water*. 2(5):667–689. <https://doi.org/10.1021/acsestwater.1c00366>
- Matta G, Kumar A, Nayak A et al (2022b) Appraisal of spatial–temporal variation and pollution source estimation of Ganga River system through pollution indices and environmetrics in Upper Ganga basin. *Appl Water Sci* 12:33. <https://doi.org/10.1007/s13201-021-01552-9>
- Mays WL, Tung Y-K (1992) *Hydro-systems engineering & management*. McGraw-Hill, New York
- Memon F, Butler D (2021) *Water consumption trends and domestic demand forecasting*. Imperial College of Science, London
- Metrological Departemnt (2022) [Accessed on 15/03/22]. Available from: <http://jmd.gov.jo/en>.
- Ministry of Environmet ME (2021) The national climate change adaptation plan of Jordan. Stagey and plan for future
- Ministry of Interior, The Hashemiate Kingdom of Jordan (2021) *Governorates and Sectors*. [Accessed on 15/01/22]. Available from: https://moi.gov.jo/EN/ListDetails/Governorates_and_Sectors/57/3.
- Ministry of Water and Irrigation (2011) Yearly reports for the period (1990–2010)
- Mohamed MM, Al-Mualla AA (2009) *Water demand forecasting in Umm Al-Quwain (UAE) using the IWR-MAIN specify forecasting Model*. Springer Science Business Media, Berlin
- Mutreja KN (1986) *Applied hydrology*. Tata McGraw-Hill, New Delhi
- The Ministry of planning and interantional coperation (2017) *M.O.P.A.I. Jordan's Way to Sustainable Development. First National Voluntary review on the implementation of the 2030 Agenda*. Amman, Jordan
- The Ministry of Water and irrigation MWI (2011) *Water strategy (The annual reprot)*
- United Nation UN (2015) *Agenda 2030 for addressing sustainable development goals*.
- World Bank (2021) The country profile, Jordan [online]. [Accessed 17/10/2021]. Available from: https://www.google.co.uk/publicdata/explore?ds=d5bncppjof8f9_&met_y=ny_gdp_mktp_cd&idim=country:QAT:ARE:KWT&hl=en&dl=en#!ctype=l&strail=false&bcs=d&nselm=h&met_y=sl_gdp_pcacp_em_kd&scale_y=lin&ind_y=false&rdim=region&idim=country:QAT:ARE:JOR:SAU&ifdim=region&hl=en_US&dl=en&ind=false.
- World Bank (2022) The country profile, Jordan [online]. [Accessed 24/08/2022]. Available from: <https://www.worldbank.org/en/country/jordan/overview>
- World Commission on Environment and Development WCED (1987) *World commission on environment and development. Our Common Future* 17(1):1–91

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