

Forecasting Domestic Water Demand Using Meteorological and Satellite Data: Case Study of Greater Beirut Area



J. Saade, S. Ghanimeh, M. Atieh, and E. Ibrahim

1 Introduction

Acknowledging the dire need for water security, the United Nations established Goal 6 of the Sustainable Development Goals (SDGs), for year 2030, on Clean Water and Sanitation. Nonetheless, the target is still behind as by 2019 around 785 million people still lack basic drinking water service (UN Statistical Commission 2019). The SDGs also acknowledge, through Goal 13: the impacts of climate change on the hydrological cycle, on various ecosystems, and eventually on the existence of humanity. In fact, temperatures in the Middle East and North Africa (MENA) region are expected to become more extreme (Atlantic Council 2019; El-Samra et al. 2017; Lange 2019; Waha et al. 2017) with a 4 °C projected increase in average temperatures by 2050 (WEF 2019). The MENA region is expected to experience hotter summers with more frequent heatwaves (ArabNews 2019; Bucchignani et al. 2018). Consequently, Lebanon's national communications revealed the pronounced impacts of the changing climate in terms of reduction in water supply and increase in water demand.

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From the water supply perspective, the anticipated cost of climate-induced drop in agricultural, domestic, and industrial water supply in Lebanon is estimated at \$ 21 Million, \$ 320 Million, and \$ 1,200 Million by 2020, 2040, and 2080, respectively— noting that the country's gross domestic product (GDP) is about 60 billion USD (MoF 2019). Similarly, the cost of climate-caused reduction in water availability for generation of hydroelectricity is estimated at \$ 3 Million, \$ 31 Million, and \$ 110 Million by 2020, 2040, and 2080 respectively (MoE 2016). A negative water balance of -518 million cubic meters (MCM) was projected for year 2030 (World Bank 2003).

Likewise, water demand is expected to change with the climate and weather conditions. At the global level, water demand is categorized as: agricultural (69%), industrial (19%), and domestic (12%). The latter has increased substantially from 50 km³/year in 1950 to more than 500 km³/year in 2010 (FAO & AQUASTAT 2015). In developing countries like Lebanon, domestic water demand (30%) comes second after agricultural water demand (61%); while industrial demand constitutes the smallest share (9%) (Hamdar et al. 2015; MoEW 2012). In fact, studies of highly congested regions of the country revealed a remarkably high domestic demand, reaching 54% in Beirut and Mount Lebanon and projected to reach up to 46% in Greater Beirut Area (GBA) in 2030 (Comair 2011; Yamout and El-Fadel 2005). In this context, the World Bank projected an increase in annual water demand from 1,257 MCM in 2003 to 2,818 MCM by 2030. This is paralleled with a shift in relative shares of sectors from 9%, 27%, and 64% to 15%, 45%, and 40% for the industrial, domestic, and agricultural demands respectively—showing the anticipated dominance of domestic water demand in the future.

Furthermore, Middle Eastern countries, including Lebanon, have specific challenges attributed to internal and cross-boundary migration. Specifically, in the context of Lebanon, the country hosts 173 refugees per 1,000 citizens, the largest number of refugees per capita worldwide (Hussein et al. 2020). This has exacerbated the already negative water balance, which is expected to peak in 2030 (Hussein et al. 2020), especially with the limited governmental strategies (Shaban 2020).

While worldwide efforts have been made to project the effects of climate change on domestic water demand (Table 1), such studies remain limited in Mediterranean countries—despite the already visible water deficit. In Lebanon, the 2010 National Water Sector Strategy (NWSS), amended in 2015 and adopted by the Ministry of Energy and Water (MoEW), projected a 30% domestic water demand by 2030 with an urban water consumption of 185 lpcd (MoEW 2010, 2012).

The NWSS tackles the water deficit problem by increasing water supply, with marginal attention to optimizing water demand. It aims at providing an additional 935 MCM of water by spring capture (65 MCM), artificial recharge of groundwater aquifers (200 MCM), and surface storage through the construction of 18 dams and 23 hill lakes (670 MCM to reach a water storage of 14.9%) (MoEW 2012).

The anticipated population growth in GBA calls for a better focus on the demand side of the water budget, taking climate change into consideration. Yet, local studies that back up this hypothesis remain limited, especially with data scarcity and lack of access to water records. This study aims at investigating the link between domestic

Table 1 Impact of weather on domestic water consumption

References	Study area	Weather parameters	Findings
Rasifaghihi et al. (2020)	Montreal, Canada	Daily minimum temperature, daily maximum temperature, daily precipitation	Definition of a temperature threshold above which the effect of weather parameters on water demand becomes considerable
Uthayakumaran et al. (2019)	Sydney, Australia	Average daily precipitation, number of days in a month when precipitation exceeds 2 mm, average daily maximum temperature, number of days in a month when temperature exceeds 300 °C, and average daily pan evaporation	Increase in water demand of 2.3% and 4.4% in short-term (up to 2040) and long-term (2060–2080) based on the A2 Scenario
Wang et al. (2017)	Yellow river basin, China	Average temperature	Under RCP 4.5, average water demand will increase by 20.2% by end of the century
Al-Zahrani et al. (2015)	Al Khobar, KSA	Minimum, average, and maximum temperature and humidity, rainfall frequency, total intensity, and wind speed (all at a daily time-step)	Temperature is the most relevant weather parameter in projecting water demand, followed by humidity, wind speed, and rainfall frequency
Chang et al. (2014)	Portland, USA	Maximum temperature and precipitation (daily and monthly), and day of the week	Maximum temperature and precipitation, combined, explain 48% of the variation in seasonal monthly water use in June and July (summer months). Including the day of the week explained 87% of the daily variation in seasonal water use
Al-ahmady (2011)	Mosul, Iraq	Season, water supply continuity, and family size	Yearly average water demand was found to be 180 ± 64 L per capita per day (lpcd), with diurnal variation between 125 ± 65 lpcd and 235 ± 64 lpcd in winter and summer

(continued)

Table 1 (continued)

References	Study area	Weather parameters	Findings
Neale et al. (2007)	British Columbia, Canada	Daily maximum temperature	Annual residential per capita outdoor water demand would increase by 6367 L for every 1 °C increase in monthly mean daily maximum temperature

Source Own elaboration

water demand and meteorological variables and targets future changes in water demand in GBA, under climate Representative Concentration Pathways (RCP) 4.5 and RCP 8.5 through utilizing water demand patterns, meteorological data, and remote sensing data. GBA is one of the most congested areas of the country and is fed by one major watershed (El Kalb river watershed) that is currently under severe stress—and is expected to suffer greatly with the future climatic changes. As such, the findings of this work are crucial to support informed decisions at the level of governmental planning and sound demand-side management of water resources in Lebanon

2 Methods and Materials

2.1 Study Area

Providing home to 2.4 million inhabitants, GBA covers an area of 253 km², including Lebanon's capital, Beirut city, that covers an area of 67 km² (Fig. 1). About 11% of the Lebanese population lives in Beirut city and another 27% of the population lives in its suburbs (CDR 2017). GBA is located east central Lebanon at an altitude ranging between 0 and 400 m above sea level and is characterized to be with a Mediterranean climate (Faour and Mhaweij 2014; OCHA 2016; UN 2020; Yamout and El-Fadel 2005). GBA is heavily populated with an average population density of 6,200 inhabitants/km². About 70% of the water demand in GBA is supplied by one main treatment station in Dbaye (Faour and Mhaweij 2014).

Dbaye station is fed by two springs; Jeita (172 MCM/year) and Kachkouch (70 MCM/year) (Badran 2016) (CDR/DAR 2014). When the discharge from the springs is low, groundwater is pumped from 26 wells in Jeita watershed and 13 wells in Beirut southern suburbs to overcome the shortage (Badran 2016; Margane and Schuler 2013). Water is conveyed through four main pipelines from Dbaye station to two stations at the north of GBA, one in central Beirut, and another one at the south of Beirut.

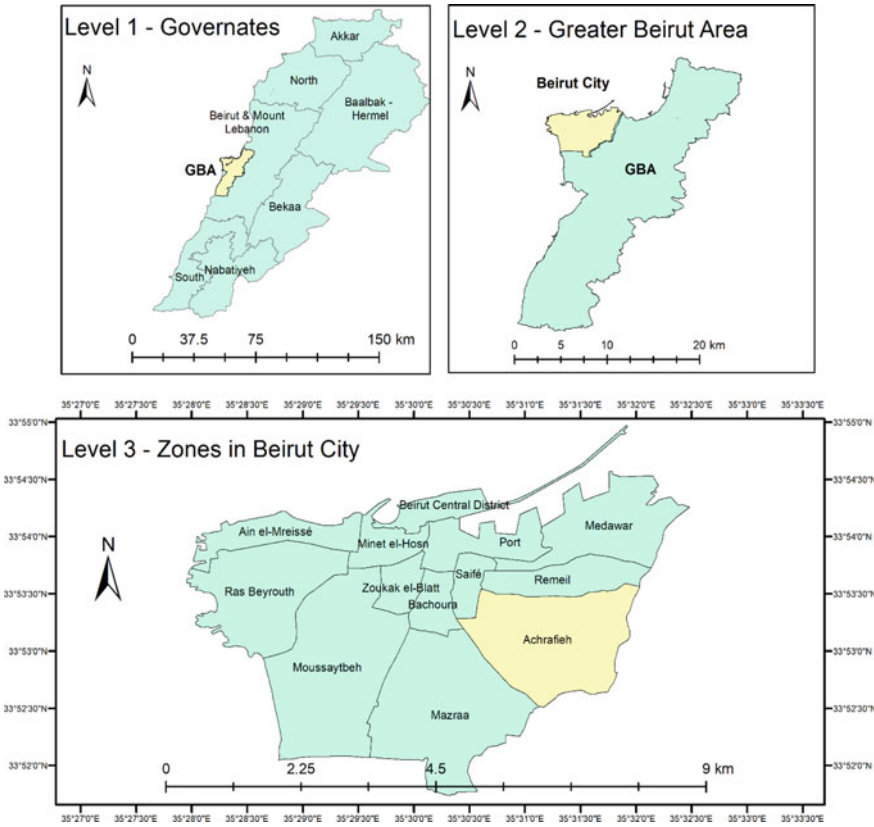


Fig. 1 Map of the study area: location of GBA in Lebanon’s map (Level 1), location of Beirut city in GBA’s map (Level 2), the zones of Beirut city (Level 3)

2.2 Water Demand Data

Given the absence of records for the GBA water demand pattern, the latter was estimated by applying the GBA local average water demand of 185 L/day/capita (CAS 2008; Jaafar et al. 2020) to the demand time pattern of Syracuse (Fig. 2). Syracuse is an urban coastal city in Italy, characterized by a Mediterranean climate with warm to hot dry summers and mild wet winters, like Beirut. Using WorldClim data, (Hijmans et al. 2005; O’Donnell and Ignizio 2012), a global gridded historical dataset (1960 to 1991), the similarity between the two cities with respect to climatic conditions can be illustrated. The data was accessed through Google Earth Engine (GEE) (Google Earth Engine 2021) with 30 arc-second spatial resolution. The mean annual temperature of the two cities are comparable where in Syracuse it is about 16 °C while in Beirut it is 20 °C (Fig. 3). The annual mean diurnal range capturing temperature fluctuation (Fig. 4) shows consistent fluctuation of 8 °C for the two cities.

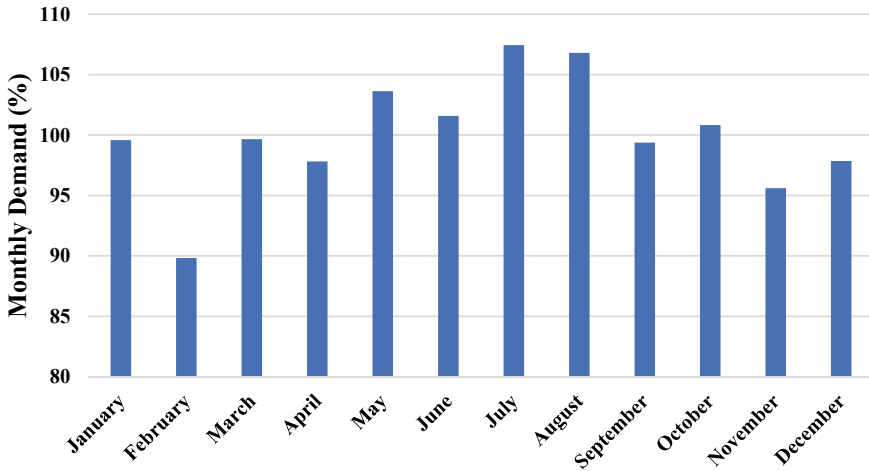


Fig. 2 Monthly demand as compared to average demand (%) in Syracuse, Italy (Campisi-Pinto et al. 2012)

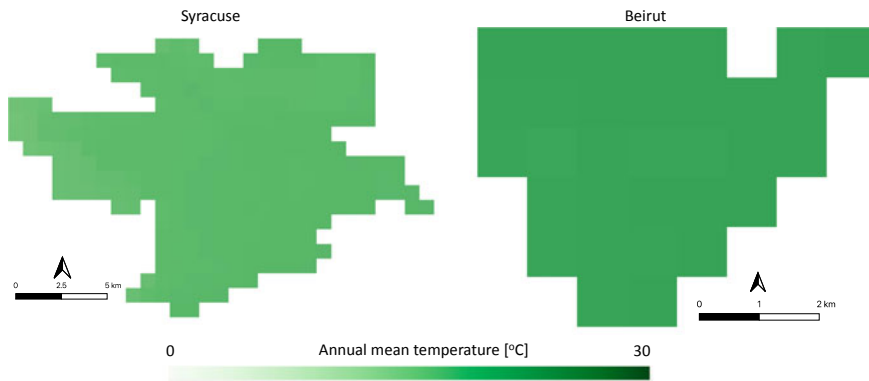


Fig. 3 The annual mean temperature of the two cities using the WorldClim dataset

Regarding precipitation seasonality, both cities exceed 80% variability (expressed as coefficient of variation) (Fig. 5) throughout the year, highlighting the Mediterranean seasons of wet winters and dry summers. Considering the similarities in weather and overall socio-economic aspects, it is assumed that similar water demand patterns would prevail in Syracuse and GBA (Campisi-Pinto et al. 2012). The demand pattern of Syracuse was averaged for the years 2002 to 2008 (Campisi-Pinto et al. 2012).

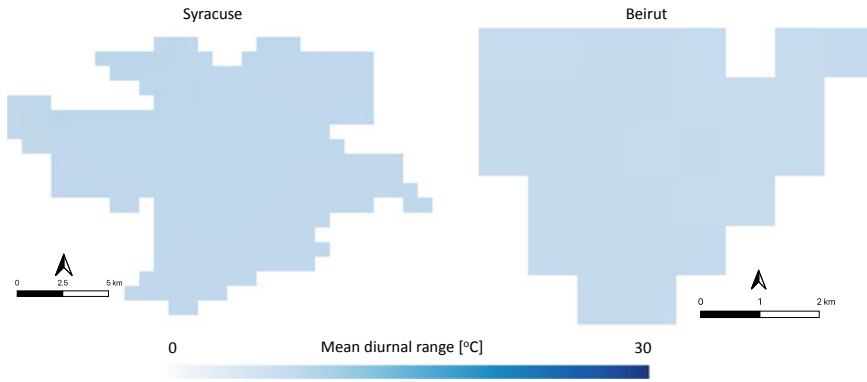


Fig. 4 The mean diurnal range of the two cities using the WorldClim dataset

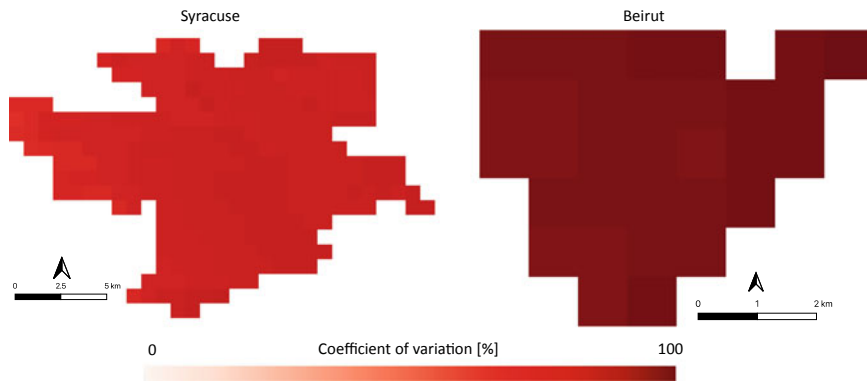


Fig. 5 The precipitation seasonality of the two cities using the WorldClim dataset

2.3 Weather Data Acquired by Ground Stations

Weather data was obtained from Achrafieh (Fig. 1) weather station in GBA for the period ranging from June 2017 to March 2019—considered to be the reference period (Litani River Authority data). The weather parameters used in this study include monthly temperature data, relative humidity, wind speed, and atmospheric pressure (Fig. 6). In addition, solar radiation (R_S), in $\text{MJ}/\text{m}^2/\text{day}$, was computed using Eq. (1) (Bou-Fakhreddine et al. 2019; Valiantzas 2013).

$$R_S \approx k_{R_S} R_A \sqrt{T_{\max} - D} \tag{1}$$

where T_{\max} is the maximum monthly temperature k_{R_S} is the radiation adjustment coefficient ranging between 0.12 and 0.25 (default value 0.17), R_A is the extraterrestrial radiation obtained according to the latitude position (FAO 2020). D is the

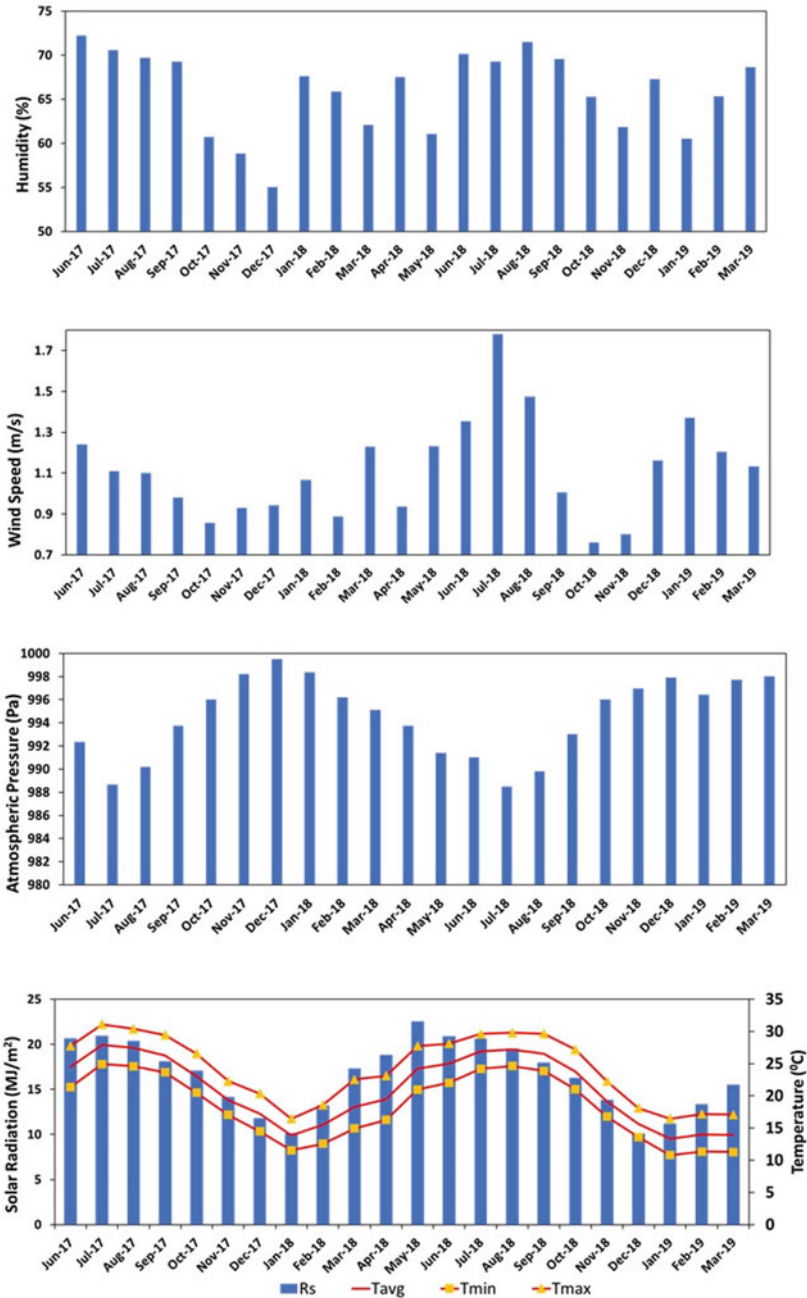


Fig. 6 GBA weather data, Achrafieh station

dew point (°C, temperature at which relative humidity reaches 100% saturation)—calculated using Eq. (2) adopted by the American Meteorological Society (Lawrence 2005), where T_{avg} is the average monthly temperature:

$$D = T_{avg} - \frac{100 - RH}{5} \tag{2}$$

2.4 Land-Surface Temperature Acquired Using Satellite Data

An essential variable in water balance analysis and land-surface processing is Land Surface Temperature (LST) that can be acquired through various approaches including in-situ measurements along with satellite observations. As data is generally scarce in Lebanon, in-situ LST data are not available, and thus, Moderate Resolution Imaging Spectroradiometer (MODIS) can provide a great opportunity in this regard. MODIS spaceborne data is the most commonly used remote sensing LST data (Phan and Kappas 2018). It is freely available, has a spatial resolution of 1 km, and continuously covers the study area as cloud cover permits (Mo et al. 2021). MODIS TERRA provides daily coverage with overpass at local times 10:30 a.m. and 10:30 p.m.

For this work, monthly mean (averaged day and night) MODIS LST values were derived for Beirut from daily MODIS data accessed through Google Earth Engine platform where a full day and night data dataset is provided (Fig. 7). The data product is MYD11A1 retrieved using the generalized split-window and day/night algorithms (Phan and Kappas 2018; Wan 2013).

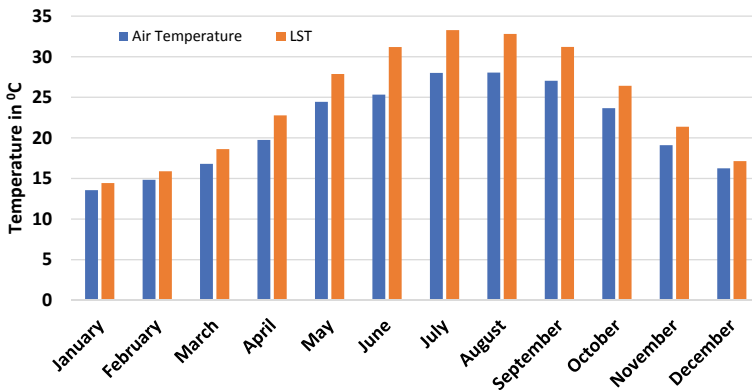


Fig. 7 Average monthly LST and air temperature for Beirut city for the period 2017–2019

2.5 Model Structure and Performance

Linear regression analysis is adopted in this study as it has been proven satisfactory to explain water demand variation in function of weather variables (Al-Zahrani and Abo-Monasar 2015; Chang and Praskievicz 2014; Gato et al. 2007) and MODIS LST (Alavipanah et al. 2016; Enriquez et al. 2019). A linear regression model is developed, of the form provided in Eq. (3). The weather parameters considered for modeling are minimum temperature (T_{\min}), average temperature (T_{avg}), maximum temperature (T_{\max}), solar radiation (R_S), wind speed (W) and relative humidity (H), and atmospheric pressure (P_{atm}), and Land Surface Temperature (LST).

$$q = \sum_{i=1}^m \beta_0 + \alpha_i \beta_i + \epsilon \quad (3)$$

where q is the specific demand flowrate (lpcd), β_0 is the regression intercept, α_i is the i th predictor's regression slope, β_i is the i th variable, where the number of selected variable is $i \in [0, m]$, and ϵ is an error term representing random noise for effect of variables not included in the model equation, referred to as a Gaussian error term (Aitken et al. 1991; Koegst et al. 2008; Rasifaghihi et al. 2020).

The performance of the model was evaluated using: (1) the p-value test of independent variables (weather parameters), with a statistical significance level of 0.05; and (2) the coefficient of determination (R^2) to assess the goodness-of-fit of the model—having a minimum of 0 (indicating that the model does not explain any of the variation in water demand) and a maximum of 1 (indicating that the water demand can be fully predicted by the model) (Eq. 4).

$$R^2 = 1 - \frac{\frac{1}{n} \sum_i^n (y_i - \hat{y})^2}{\frac{1}{n} \sum_i^n (y_i - \bar{y})^2} \quad (4)$$

where \hat{y} is the forecasted water demand, y_i is the actual water demand, \bar{y} is the mean actual water demand, and n is the number of observations.

The analysis considered simple linear regression (i.e., $m = 1$) and assessed the correlation of demand with each variable. On the other hand, a multivariate linear regression was also carried out, and the selection of the number of independent variables aimed at reducing multicollinearity. The Variation Inflation Factor (VIF) (Eq. 5) was used to select the suitable variables, where (Akinwande et al. 2015),

$$VIF = \frac{1}{1 - R^2} \quad (5)$$

VIF thus iterated among the variable and excluded one variable causing multicollinearity at a time. The multivariate regression was implemented using the Classification and Regression Training (CARET) package in R (Kuhn 2008).

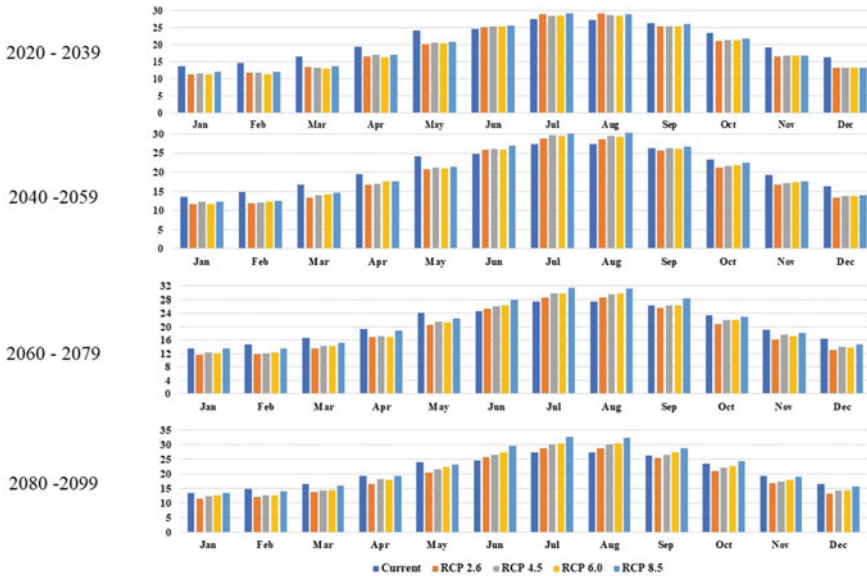


Fig. 8 Current versus future monthly average temperature (T_{avg}) under RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 during 2020–2039, 2040–2059, 2060–2079, 2080–2099 (World Bank 2020)

2.6 Climate Change Projections

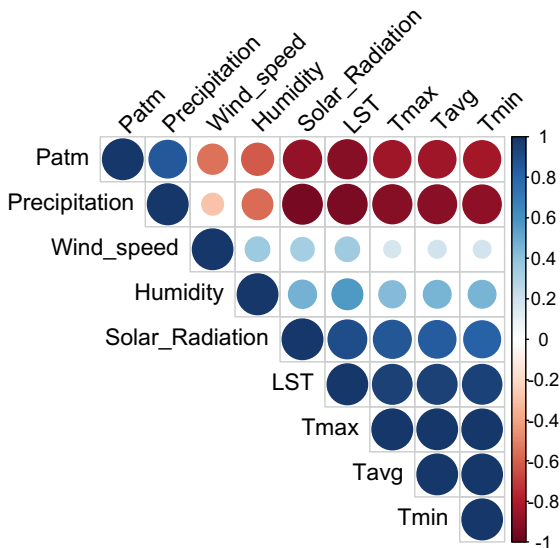
Climate change projections for minimum, average, and maximum temperatures were obtained from the Climate Change Knowledge Portal for four 20-year periods: 2020–2039, 2040–2059, 2060–2079 and 2080–2099 (World Bank 2020) (Fig. 8). Those were simulated using the Beijing Climate Center Climate System Model (BCC—CSM 1), adopted in several scholar articles (Wang et al. 2018; Jun Wang et al. 2017).

3 Results and Discussion

3.1 Water Demand Models

The independent variables, including weather and LST datasets, were mostly correlated (Fig. 9). Wind speed and humidity showed the lowest correlation with other variables, yet correlations were still significant. The four-seasoned Mediterranean climate where rainfall is highest in the cold winters is apparent in the high negative correlations between precipitation and each of air temperature and LST.

Fig. 9 Pairwise correlation matrix plot of the independent variables indicating Spearman's correlation as per the color legend. All correlations were statistically significant (p-value < 0.05)



Linear regression relationships were established between individual weather parameters (independent variables) and water demand (the dependent variable) (Fig. 10). The analysis of the resulting models revealed that all weather parameters were statistically significant (p-value < 0.05) at the exception of relative humidity (p-value = 0.065) (Table 2). The negative correlation between atmospheric pressure and water demand showed the best fit with R² value of 0.58, resulting in a linear regression model with the least error (i.e. minimum difference between predicted and observed water demand). The next best fit regression models were those based on temperature (T_{avg}, T_{min}, T_{max}) as independent variable. They showed positive correlations with R² values of 0.52, 0.52, and 0.50, respectively. Similar levels of accuracy were reported: 0.57 to 0.70 for calibration and from 0.56 to 0.68 for validation (Al-Zahrani and Abo-Monasar 2015) and 0.33 to 0.38 (Chang and Praskievicz 2014). Wind speed showed low correlation with water demand (R² = 0.25), thus proven inadequate to explain the variation in water demand.

For the multi-variable regression analysis, the VIF iterative test with a threshold for excluding variables of VIF > 10, recommended only preserving solar radiation, T_{min}, humidity, and wind speed, where their VIF's in this final subset of variables were 3.37, 3.22, 1.43, and 1.24 respectively. The data were then partitioned 70% and 30% for training and validation, respectively, and the following equation (Eq. 6) was achieved, with an R² exceeding 0.7 and high significance of all variables, except for solar radiation where p-value > 0.1 (Table 3).

$$Demand = 176.3 + 0.5R_S + 1.5T_{min} - 0.68H + 13.4W \tag{6}$$

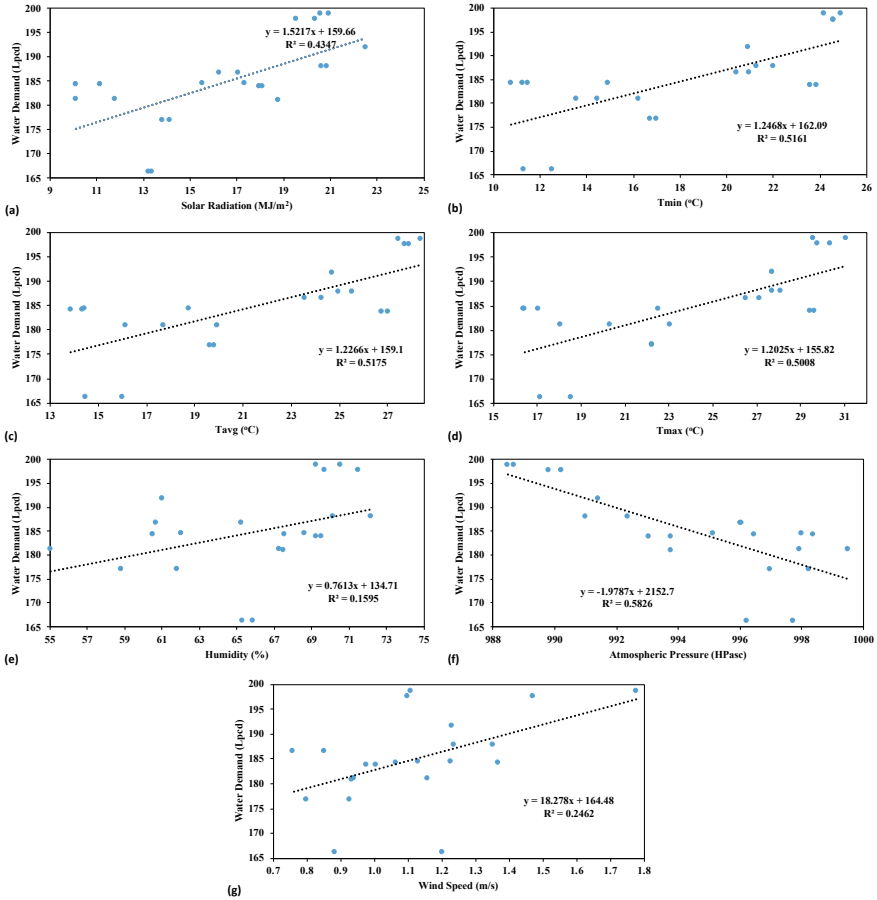


Fig. 10 Linear regression relationships between water demand and weather variables: **a** solar radiation, **b** minimum temperature, **c** average temperature, **d** maximum temperature, **e** humidity, **f** atmospheric pressure and **g** wind speed

Table 2 Model performance and statistical significance of weather variables

Statistical measures	R _s	T _{avg}	T _{min}	T _{max}	H	P _{atm}	W
R ²	0.4340	0.5170	0.5160	0.5000	0.1590	0.5825	0.2460
p-value	0.0008	0.0002	0.0002	0.0002	0.0655	0.00001	0.0188

where RS is the average monthly solar radiation in MJ/m², T_{min} is the minimum air temperature in °C averaged monthly, H is the average monthly relative humidity in %, and W is the average monthly wind speed in m/s. Figure 11 shows the partial regression plots detailing the relationship between the demand and each predictor

Table 3 Multivariable regression results

Residuals				
Min	1Q	Median	3Q	Max
-6.09	-3.38	-0.04	3.33	9.40
Coefficients				
Variable	Estimate	Std. error	t-value	Pr (> t)
Intercept	176.33	18.43	9.57	~0***
Solar radiation (MJ/m ²)	0.50	0.70	0.72	0.48
T _{min} (° C)	1.53	0.48	3.19	0.07**
Humidity (%)	-0.68	0.35	-1.96	0.07
Wind speed (W)	13.41	5.75	2.33	0.04*

Signif. Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '.' 1

Residual standard error: 5.142 on 12 degrees of freedom

Multiple R-squared: 0.7757, Adjusted R-squared: 0.701, F-statistic: 10.38 on 4 and 12 degrees of freedom, p-value: 0.0007197

variable, while controlling for the presence of the other variables in the model. These plots were produced using the “car” package in R (Fox and Weisberg 2019).

3.2 Forecasted Water Demand

Considering that forecasts of future solar radiation wind speed, and humidity levels in Lebanon are lacking, water demand in GBA was projected using the linear regression models for minimum, average and maximum temperature (T_{\min} , T_{avg} and T_{\max}) (Table 3). These parameters were also adopted in other studies for forecasting the impact of the climate change on residential water demand (Al-Zahrani and Abo-Monasar 2015; Rasifaghihi et al. 2020).

Four periods (2020–2039, 2040–2059, 2060–2079, 2080–2099) were simulated. Climate forecasts revealed higher temperatures during summer months (June, July, August) and lower temperatures during winter months (December, January, February), compared to the reference period (2017–2019). As expected, RCP 8.5 showed the highest increase in temperature (Fig. 8). Consequently, the simulation results, using T_{\min} , T_{avg} and T_{\max} models, showed an increase of per capita water demand during summer and a decrease during winter. All three models showed very similar trends and the forecasted water demand values were close. For comparison purposes, the benchmark period (2017–2019) was also simulated, and the values are compared to the forecasted demand for all four future periods; the subsequent analysis considers the range of water demand predicted by the three temperature-based models.

On average, the *yearly demand* is forecasted (by the three temperature models) to increase under all scenarios, except RCP 2.6 (Fig. 12). Furthermore, a temporal

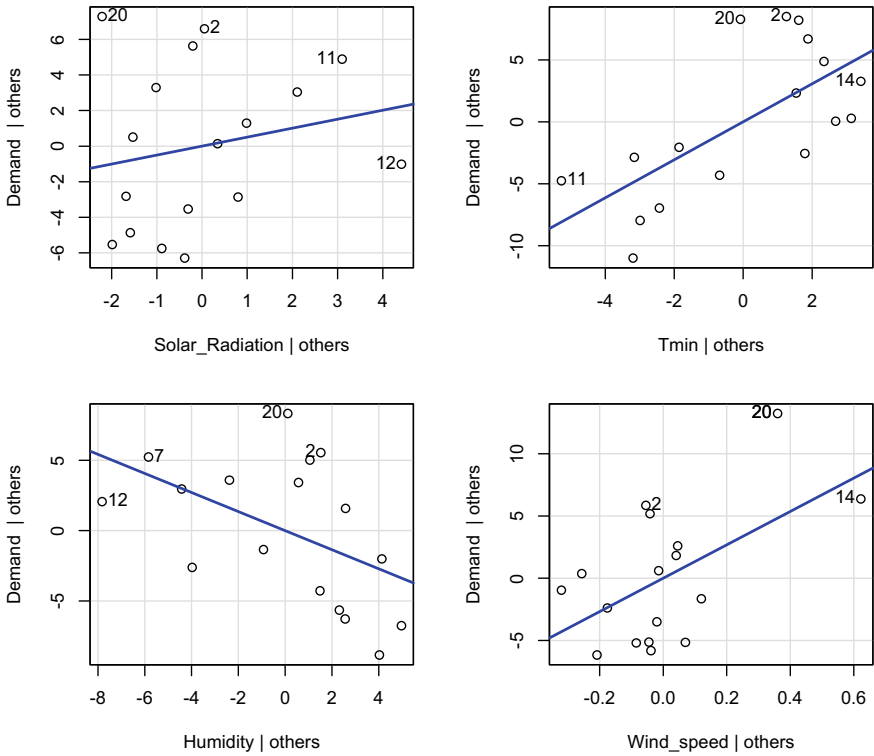


Fig. 11 Partial regression plots showing the effect of adding a new variable to a model by controlling the effect of the predictors in use

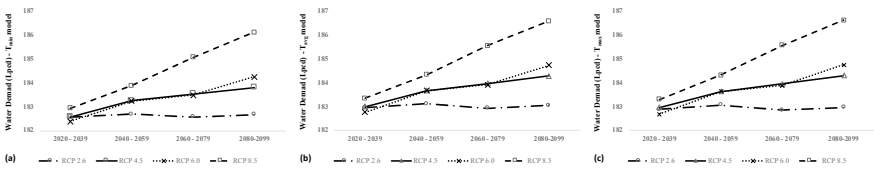


Fig. 12 Average yearly water demand (lpcd) under RCP 2.6, 4.5, 6.0, and 8.5 for the three models: **a** T_{min} , **b** T_{avg} and **c** T_{max}

shift in extreme demands, i.e., minimum and maximum monthly average demand, is expected. The former is expected to gradually shift backward, from February to January; while the latter is anticipated to gradually move forward from July to August—similarly to previously reported observations (Ghimire et al. 2016). This can be attributed to the anticipated climatic changes in terms of (1) shift in seasons, (2) longer dry periods, and (3) more intense yet shorter wet periods (Giorgi and Lionello 2008; Schilling et al. 2012).

The *maximum water demand*, occurring during the dry season, is anticipated to increase by 1 to 2 Lpcd on the short term (2020–2039) and 2 to 6 Lpcd on the long term (2080–2099) (Fig. 13b). Similarly, the *minimum water demand*, occurring during the wet season, is expected to decrease by about 3 Lpcd on the short term (2020–2039). But it will rise again and the difference with respect to current values will gradually drop to 2, 1 and 0 Lpcd, under RCP 4.5, 6 and 8.5, respectively, by the end of the century (Fig. 13a). To note that, under RCP 2.6, minimum and maximum temperatures remain fairly constant throughout the century.

3.3 Impacts on Total Demand

The total population size of GBA was forecasted by the Greater Beirut Water Supply Augmentation project (CDR 2017). It is expected to reach 3.5 million by 2035, compared to a current population of 2.0 million. Thus, about 46% increase in domestic water demand is expected due to population growth alone, leading to a yearly deficit of 227.7 MCM (CDR 2017).

On top of that, this study showed that climate change would cause an additional increase in domestic demand (*during the dry period*) of 45–90 thousand cubic meter per month on the short term (2020–2039) and 90–270 thousand cubic meter per month on the long term (2080–2099), as a best-case scenario as without considering population growth. Despite the fact that these figures do not seem substantial compared to the total yearly deficit, they are expected to occur at the most sensitive time of the year. In fact, the dry period is the most water stressed time of the year. Commonly, the water supply is not sufficient and most citizens buy tanked water at high prices and without any quality control measures. Thus, the expected monthly increase in water demand would result in an acute deficit during summer, accompanied by economic impacts and a possible surge in water-borne diseases. The latter was already proved to be substantial in Beirut due to the anticipated temperature increase alone (Yamout and El-Fadel 2005).

4 Conclusions and Recommendations

This study addresses one component of the anticipated socio-economic impacts of climate change on GBA, that is the increase in water demand. When combining all effects, including those of rising temperatures, reduced water availability, increased heat waves and heat island effect, among others, the anticipated additional burden looks disastrous—considering the already high vulnerability of GBA. In response, the Lebanese national and regional water authorities often advocate measures to ensure additional supply. Examples of planned projects for increased supply to GBA include: Awali river conveyor, Bisri dam, Janneh dam and Damour dam.

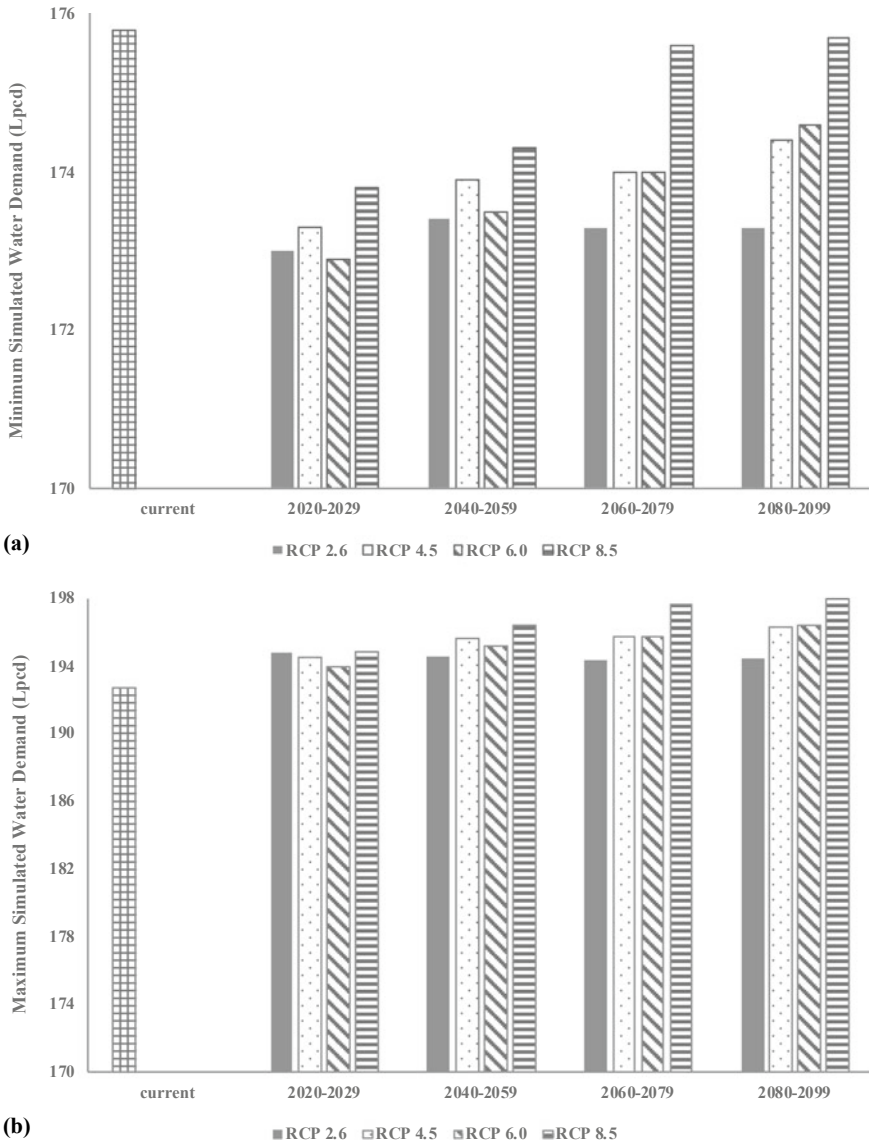


Fig. 13 Simulated water demand (lpcd) under RCP 2.6, 4.5, 6.0, and 8.5 for the three models: **a** minimum monthly average, **b** maximum monthly average

In such a data-scarce environment, Lebanon lacks detailed analysis of its water demand and influencing factors. This work investigated the link between domestic water demand patterns with monthly meteorological data and remotely sensed land surface temperature. The water demand pattern was found to be well described through minimum air temperature, humidity, wind and solar radiation, providing R^2 exceeding 0.7. Temperature was found to be highly correlated to water demand, and as it is the only dataset providing forecasts in the context of scenarios of climate change, it was used to forecast domestic water demand. Without considering an increase in population, an increase of 45–90 thousand cubic meter per month on the short term (2020–2039) and 90–270 thousand cubic meter per month on the long term (2080–2099) is expected for Beirut.

With domestic demand making up 76.9% of the total demand (Hamdar et al. 2015; MoEW 2012), assuming no agricultural water demand in GBA, attention should be drawn to the *reduction of domestic water demand*. This is especially true in the case of GBA where network losses are high (average of 47.5% in Lebanon compared to 35% global average) (MoEW 2012). In fact, a smart metering pilot test performed over a Achrafieh zone, as part of the Greater Beirut Water Supply Project, showed network losses of 52.4% (Bambos 2018). The average deficit between actual supply and demand, at the study zone, was found to be 53.5 Lcpd, equivalent to 28.95% of the demand.

Yet, efficient planning for reduced water demand calls for *improved availability of accurate and systematic data*. The whole country, including GBA, lacks actual demand figures due to (1) incomplete metering infrastructure and (2) absence of governmental monitoring and control of private water distribution businesses. Similarly, losses and actual water supply (reaching the consumer end) are not tracked by water authorities.

Acknowledgements We would like to thank Eng. Mary Saade, Eng. Antoine Zoghbi and Eng. Habib El Asmar from Beirut and Mount Lebanon Water Establishment (EBML) for helping in the provision of the water supply data. We would also like to thank Dr. Ziad Rached from the faculty of applied sciences at NDU for his insight on time series analysis.

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