

TEMPORAL SCALE IMPACTS OF WEATHER VARIABLES ON URBAN WATER DEMAND

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Abstract

In this paper, two weather variables, temperature and rainfall, were analysed for their temporal scale impacts on urban water demand in the Metropolitan Waterworks Authority (MWA) service area, including Bangkok, Nonthaburi and Samut Prakan provinces. The multiple linear regressions were used for analysing impacts based on n-day averaged data and various time scales. The results indicated that while temperature strongly impacted on an increase in the urban water demand, rainfall weakly contributed to reducing them. Based on the temporal scale impacts, temperature should be included in all MWA urban water demand forecasting whereas rainfall should only be included for a mid to long term forecasting. An average surplus of water supply for short-term water demand is approximately 290,000 m³/day while for mid- to long-term water demand is approximately 4.74 MCM/month. Temperature increment from climate change will increase MWA daily demand forecast between 50,000-140,500 m³/day in 2047.

Keywords: Urban water consumption, multiple temporal scales, weather impact

Introduction

The global water demand for domestic uses is expected to increase significantly, especially in cities and countries with developing economic growth (WWAP, 2014). It was projected that by 2050, 68% of the world's population would be in urban comparing to 30% in 1950 (United Nations, 2018). Bangkok as Thailand capital city and its vicinity provinces (Nonthaburi and Samut Prakan provinces) are growing rapidly, the water supply provided by Metropolitan Waterworks Authority (MWA) has increased from 4.76 million cubic meters per day (MCM/day) in 2007 to 5.68 MCM/day in 2019. Understanding and forecasting the water demand is one of the challenging tasks for MWA. According to the MWA plan and

development internal report, the water demand was predicted from 2007 to 2047 based mainly on population and economic growth. However, urban water demand is influenced by many other variables besides population such as weather, price, etc. (House-Peters and Chang, 2011).

Urban water demand can be modeled or forecasted by many methods from rudimentary methods such as unit water demand analysis to more complex methods such as artificial neural networks (Donkor *et al.*, 2014). Donkor *et al.* (2014) have reviewed methods and models on urban water demand forecasting from selected journal papers from 2000 to 2010. They found that the most frequent methods for forecasting urban water

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demand have been time-series regression models while artificial neural networks have been applied to forecast water demand with better performance due to their ability to capture nonlinearities. Nonetheless, artificial neural networks cannot describe the impacts of each input variable on outputs as the networks seek to learn patterns between inputs and outputs (Minns and Hall, 1996).

Urban water demand is influenced by many variables based on whether it is analyzed on temporal or spatial bases. For weather related variables, temperature and precipitation are the most common ones. Impacts of climate and weather variables on urban water demand have been studied for nonlinear (eg. Miaou, 1990), linear (eg. Goodchild, 2003) or a combination of both linear and nonlinear effects (eg. Toth *et al.*, 2018). Only a few studies such as Polebitski and Palmer (2010) and Adamowski and Karapataki (2010) had discussed the magnitude of weather variable impacts. However, how impacts are changed by time scales have not been explicitly studied. Urban water demand is sensitive to time scale, especially seasonal time scale as pointed out by House-Peters and Chang (2011).

Over the past 40 years, 1970-2009, an average temperature rise in Thailand is about 0.024°C per years (TRF, 2016). Especially in the metropolitan areas where a dome heat island or urban temperature is higher than outside (Limsakul and Limjirakan, 2012). Arifwidodo and Tanaka (2015) who studied the characteristics of urban heat island in Bangkok found that the average amount of temperature in Bangkok is 0.8°C higher than outside the city.

In this study multiple time scales and n-day averaged of two weather variables, temperature and rainfall, have been related to MWA water demand. We analyzed the effects from different time scales of these weather variables on the water demand. We detrended and normalized the water demand for a better understanding of the impacts. As the average temperature of Bangkok is constantly rising, the results of this study others than give a light on temporal scale impacts on urban demand, they will also help the MWA agency to acknowledge the problems and prepare a feasible solution.

Materials and Methods

Study Area and Data

Metropolitan Waterworks Authority (MWA) is a water utility organization providing potable water for Bangkok and its vicinity areas with more than 10 million population. MWA provides approximately 2,000 million cubic meters of potable water in 2019. Our study area is the MWA service

area covering Bangkok, Nonthaburi and Samut Prakan provinces. Weather dataset were obtained from 5 meteorological stations, namely Bangkok (455201), Khlong Toei Port (455203), Bangna (455301), Don Muang Airport (455601) and Samut Prakan (429301) as shown in Figure 1.

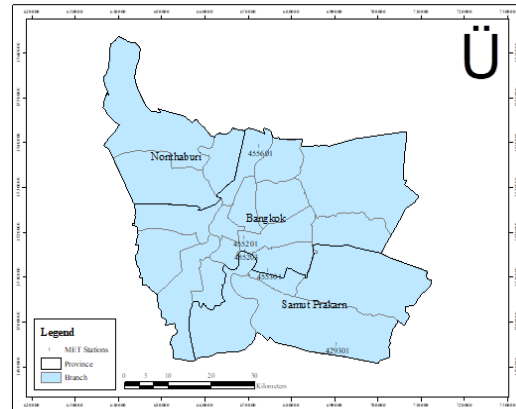


Figure 1. Study Area and meteorological stations

MWA provides a water demand dataset consisting of daily water discharge and monthly water demand. To obtain daily demand, we assumed daily water loss by subtracting monthly water discharge with water demand and averaging it for daily water loss. Various temporal scales of water demand are then based on these daily data. Seasonal data are average of daily data during a range of each season. According to Meteorological Department (MET), Thailand can be divided into 3 seasons. Summer is between 16th February and 15th May, rainy season from 16th May to 15th October and winter from 16th October to 15th February. The period of the data is between 1st October 2007 to 30th September 2017, totaling of 10 years. Hence, the seasonal study period starts from winter of 2007 to rainy season of 2017.

For weather data, MET provides daily temperature and rainfall data. We used average data from 5 MET stations in the study area, except before 2013 when Samut Prakan Station (429301) has not measured data yet.

By examining the demand data, we found extremely low water demand during October 2011-January 2012 which was caused by a mega flood in 2011. We also found that during long holiday (more than 3 days) water demand was significantly lower than normal day. Therefore, we did not include those demand data in our study. For rainfall data, the trace amount of rainfall, which was recorded as “T” in the database, was treated as zero rainfall. Detailed information of urban water demand and weather datasets are described in Table 1.

Table 1. Detailed Information of Urban Water Demand and Weather Data

Item	Water Demand (MCM/day)			Temperature (°C)			Rainfall (mm/day)		
	Max	Min	Average	Max	Min	Average	Max	Min	Average
Daily	4.30	3.04	3.67	34.15	18.20	29.20	115.90	0.00	5.25
Weekly	4.22	3.13	3.67	33.00	22.94	29.19	31.26	0.00	5.18
Biweekly	4.14	3.14	3.67	32.70	23.56	29.19	27.25	0.00	5.19
Monthly	4.11	3.23	3.67	31.90	25.12	29.20	17.65	0.00	5.15
Bimonthly	4.04	3.22	3.67	31.17	26.45	29.19	14.55	0.00	5.10
Quarterly	4.01	3.34	3.67	31.37	27.44	29.18	11.52	0.37	5.24
<i>Seasonally</i>									
Summer	4.03	3.54	3.81	31.10	28.72	30.24	5.89	0.72	2.81
Rainy	3.90	3.42	3.68	29.90	29.06	29.47	10.75	6.33	9.00
Winter	3.80	3.32	3.58	29.02	26.80	28.05	3.50	0.69	1.86

Methodology

Normalized water demand

To investigate the impact of weather on water demand, we assumed that all other major variables except our weather-related variables present in the water demand as time series trends. After removing these trends, we then can relate weather data to the urban water demand. The time series model of the urban water demand can be expressed as:

$$D_t = \alpha_0 + \sum_{j=1}^v \alpha_j t^j \quad (1)$$

where D_t is the water demand at time t , α_0 is the regression intercept and j is a polynomial term in the trend component, v is a polynomial order and α_j is the trend coefficient. For our model, we used v as 1 for a linear trend component. We considered that all growth-related variables such as population, economics, and an urban growth are included in the trend. After the model is constructed with daily data, we removed this trend by subtracting it from water demand such that

$$\hat{D}_t = D_{obs,t} - \alpha_1 t \quad (2)$$

where $\hat{D}_t$ is the detrended water demand at time t . We then tested the stationarity of $\hat{D}$ by using an Augmented Dickey-Fuller (ADF) test (Said and Dickey, 1984). The test is aimed for an unknown lag time autoregressive-moving average model. However, for this study, a k -lag autoregressive model, AR(k), is considered and can be given by the equation:

$$\Delta \hat{D}_t = \alpha \hat{D}_{t-1} + \sum_{j=1}^{k-1} \beta_j \Delta \hat{D}_{t-1} + e_t \quad (3)$$

where Δ is the difference operator, e_t is a white noise sequence of random variables, α and β_j are the coefficients. For autoregression models, Hall (1994) concluded that a lag could be estimated by any

methods including Akaike info criterion (AIC) to gain the power of ADF test if the series have moderate to large-sized samples. Since our series have large-sized samples with more than 3,000 samples, the optimal lag was therefore based on AIC. The null hypothesis of the unit root test is that the time series data has a unit root and is not stationary. If the null hypothesis is rejected then the time series data is stationary.

After proving for its stationarity, we normalized the detrended daily water demand by dividing them with α_0 from Equation (1) in order to make it as a ratio instead of a value. This normalization process would give an easier understanding on impact of weather variables to the water demand.

$$D'_t = \hat{D}_t / \alpha_0 \quad (4)$$

where D'_t is the normalized water demand.

Impact of weather data on water demand

A multiple regression is a simple linear regression extension. It is normally used when we need to predict based on two or more variables. Results in one variable can be predicted from the others. The variables we predict are called dependent variables or target variables while the input variables are called independent variables or determinants. A linear relationship is assumed between two variables. Linear regression is a commonly used statistical analysis in water demand while nonlinear regression is used to various growth models (Donkor *et al.*, 2014).

After removing the long-term trend and normalizing the detrended data, the influences of weather-related variables on normalized water demand can be described by a multiple linear regression model which is based on the basis of relationship between water demand and its determinants. Our model can be expressed as:

$$D'_t = \beta_0 + \sum_{i=1}^n \beta_i x_{i,t} \quad (5)$$

where D_t' is the normalized water demand at time t , β_0 is the regression intercept and i is an index of i^{th} independent variable, n is the number of variables, and $x_{i,t}$ is a value of i^{th} independent variable at time t . Our independent variables are temperature and rainfall. Time scales used in this study are daily, weekly, biweekly, monthly, bimonthly, quarterly and seasonally time scales. To further analyze time scale impacts on water demand, we performed an n -day averaged weather variables and normalized water demand by varying n from 1 to 90 days.

Results and Discussion

Normalized Water Demand

In order to find the urban growth trend of daily water demand, a simple time series model, equation (1), was adopted. We found the relationship to be

$$D_t = 3.384571267 + 0.0001569626t$$

Hence, α_0 is 3.384571267 and t is time in day from 1st October 2007. The growth trend of the water demand is 0.0001569626 MCM/day. We removed this trend for a zero slope adjustment by subtracting it from water demand to obtain the detrended water demand, $\hat{D}_t$.

To test whether the trend were removed, we performed the ADF test with an AIC criterion on the detrended water demand. The ADF test can be performed on three regression models: (1) a model with no constant and no linear trend, (2) a model with a constant and no linear trend, and (3) a model with a constant and a linear trend. In our case, it is obvious that there is a constant. Hence, we performed the ADF test on the second model with a hypothesis that the model is non-stationary. We can reject the hypothesis (a model is stationary) if an absolute value of Tau statistic (τ) is greater than the absolute value of Tau critical value (τ_c). We found that the AIC criterion gave a 28 days lag time with the lowest absolute Tau statistic being 7.042 and P-value less than 0.01. The critical Tau statistic for

a 0.01 significant level is 3.43. Hence, the detrended water demand is stationary in time.

We then normalized each daily detrended water demand by dividing it with $\alpha_0 = 3.384571267$. Consequently, we had the normalized water demand, D_t' , that the value ranging between 0.7 to 1.2. It can be seen from Table 1 that the average temperature for the summer season is 30.24°C with the average water demand being 3.81 MCM/day while the average temperature during the winter is 28.05°C, and the water demand is down to 3.58 MCM/day.

Temporal Scale Impact Analysis

Impacts of two weather variables, temperature and rainfall, were analyzed using a multiple linear regression. Table 2 shows the results from the regression. The statistics in the table are composed of coefficients of the regression variables, T-stat and P-value. The coefficient values show how strong the impact of each variable on the normalized water demand. For example, a change in 1°C of temperature has 1.520, 1.647, 2.027 and 2.284 percent changes in the water demand for daily, weekly, monthly and quarterly time scale, respectively. T-stat values show how large the coefficients compare to the standard error. The larger number of T-stat indicates the significance of the variable. The T-stat values are then compared with the Student's t distribution to determine the P-values. The P-values indicate the probability that the variables have no effect on the dependent, the normalized water demand in this case.

According to P-values in Table 2, the temperature and rainfall had a significant influence on urban water demand on every time scales. Based on the coefficients in the Table, the temperature had a positive impact on the water demand meaning higher temperature resulting in higher water demand while the rainfall had a negative impact on the demand meaning higher rainfall resulting in lower water demand.

The increase of temperature by 1°C affected from 1.520% increase of water demand for daily

Table 2 Results of multivariable linear regression of normalized water demand (D) to average temperature (T) and rainfall (R)

Normalized Water demand	Coefficient			T-stat		P-values	
	T (1°C)	R (1/(mm/day))	Intercept	T	R	T	R
Daily	0.01520	-0.00017	0.55706	40.52236	-2.94643	0.00000 ^a	0.00324 ^b
Weekly	0.01647	-0.00066	0.52196	16.09503	-2.66011	0.00000 ^a	0.00808 ^c
Bi-weekly	0.01829	-0.00119	0.47174	12.49607	-3.21011	0.00000 ^a	0.00153 ^b
Monthly	0.02027	-0.00164	0.41735	9.15040	-2.51238	0.00000 ^a	0.01340 ^c
Bi-monthly	0.02332	-0.00303	0.33548	10.20322	-4.54135	0.00000 ^a	0.00003 ^a
Quarterly	0.02284	-0.00380	0.35353	7.98810	-4.14403	0.00000 ^a	0.00021 ^a
Seasonally	0.02377	-0.00291	0.32237	8.62109	-3.37838	0.00000 ^a	0.00223 ^b

^a significant at 0.001 level, ^b significant at 0.005 level, ^c significant at 0.01

time scale to 2.284% increase for quarterly time scales. Whereas, the increase of rainfall by 1 mm/day affected only from 0.017% decrease of water demand for daily time scale to 0.38% decrease for quarterly time scales. Hence, temperature had more impact than rainfall.

Polebitski and Palmer (2010) studied a residential water demand forecasting using a linear regression model based on bimonthly data. They found that a 10% increase in temperature resulted in 4-10% increase in water demand depending on the month. As an average temperature in our study area is around 29°C, a 10% increase in temperature would be 2.9°C. The 2.9°C change resulted in 6.76% increase in water demand for bimonthly time scales in our study which were in the same range as their study.

Polebitski and Palmer (2010) also found that a 10% increase in rainfall resulted in 2.5% decrease in water demand during summer month and comparatively small decrease during other months. Again, as an average rainfall in our study area is about 5 mm/day, a 10% increase in rainfall would be 0.5 mm/day. Hence, in our study the 0.5 mm/day increase of rainfall would result in only 0.151% decrease in water demand for bimonthly time scale in our study which were a lot less than in their study. One of the reasons could be that we used all rainfall data including zero and little rainfall in our analysis. Polebitski and Palmer (2010) also found that during winter time, rainfall were significant with small impacts, albeit little rainfall during the winter time. Hence, a suggestion of removing rainfall variable during the winter time was made for improving their model. Adamowski and Karapataki (2010) who studied on the peak weekly water demand also suggested that the use of the occurrence or non-occurrence of rainfall was better in their model than the actual rainfall amount. This is in agreement with our finding that time scale of data did impact on how strong the weather variables on water demand. Our result of 0.066% change from weekly time scale also suggests that the rainfall amount has very low impact even though the presence of rainfall is significant in the model. It can be seen from our results that the impact of rainfall is 3.9 and 9.6 times stronger when the time scale was changed from daily to weekly and monthly, respectively. Hence the amount of rainfall becomes significant when the time scale becomes larger.

We plotted the normalized water demand against average temperature and average rainfall as shown from Figure 2 to Figure 3. Figure 2 shows that a trend of daily, weekly, monthly and quarterly normalized water demand increasing along average temperature. The daily and weekly data were ranged

around 27-32°C, making it a 5°C range. According to Table 2, a 1°C increase resulted in 1.520-1.647% increase of daily and weekly water demand. Hence a 5°C range could result in 7.6-8.2% change of daily and weekly water demand. An average water demand in MWA area is 3.67 MCM/day. Hence a 7.6-8.2% change is 278,920-302,205 m³/day. This is an amount that MWA could be used for their extra supply especially during high temperature seasons.

For monthly and quarterly water demand, the data were ranged around 28-30°C making it only a 2°C range. According to Table 2, a 1°C increase resulted in 2.027-2.284% increase of monthly and quarterly water demand. Hence a 2°C range could result in 4.054-4.568% change of monthly and quarterly water demand. An average monthly and quarterly water demand in MWA area is 110 MCM/month, consequently a 4.054-4.568% change is approximately 4.46-5.02 MCM/month. Therefore, MWA should prepare for an extra water supply of 4.46-5.02 MCM/month during high temperature months.

From Figure 3, the impacts of rainfall on daily and weekly water demand are small. There is no need to include rainfall for short term planning of water demand. However, monthly average rainfall is 5.16 mm/day and can be high as 9.0 mm/day

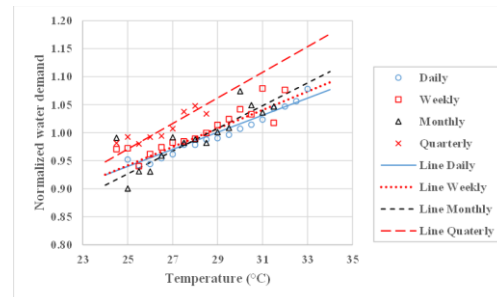


Figure 2. Impacts of temperature on normalized water demand

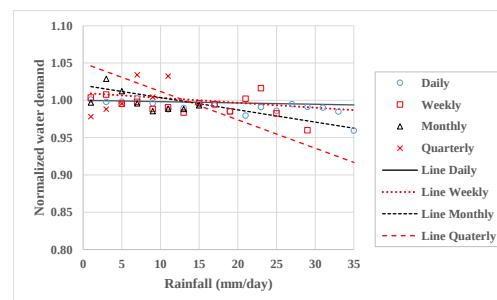


Figure 3. Impacts of rainfall on normalized water demand

during rainy season. A 1 mm/day results in 0.164% decrease of water demand. Hence 9.00 mm/day during rainy season would result in 1.47% decrease of water demand. So, during rainy season MWA could reduce its water supply by 1-2 percent for a monthly plan. Moreover, the impact of rainfall on quarterly water demand is double of the monthly water demand. A 1 mm/day results in 0.380% decrease of water demand. A 9.00 mm/day change during rainy season would result in 3.42% decrease of water demand. Therefore, for a longer time plan during rainy season MWA could reduce its water supply by 3-4 percent.

Figure 4(a) shows a seasonal normalized water demand plot with temperature. All data seems to fit quite well with the multiple linear regressions. Hence, Figure 4(b) were plotted to show different season data. Surprisingly, all three season data with different temperature ranges follow the same trend line nicely. Normally, when a season is considered in water demand forecasting or modeling, data are separately treated by a season, e.g. Polebitski and Palmer (2010). However, based on our results, it is not necessary or compulsory to separate data by a season to consider seasonal effect of weather variables on water demand.

The magnitudes of temperature impact from daily to weekly, monthly and quarterly time scales were in the order of 1.1-1.6, whereas, the magnitude of rainfall impact is in the order of 3.8-21.8. Therefore, to analyze temporal scale impacts in details, we performed n-day averaged temperature, rainfall and normalized water demand by varying n from 1 to 90 days. The coefficient of the regression were multiplied by 100 to be a percent change of normalized water demand. Figures 5(a) and 5(b) show how temperature and rainfall impacts were changed by time scales, respectively. The relationship for temperature can be expressed in a power form with a coefficient of determination (r^2) = 0.9093 as

$$C_t = 1.4609t^{0.1014}$$

Where C_t is a percent change of normalized urban demand per degree Celsius and t is a time scale in days. From Figure 5(a), the impacts were changed rapidly during 1-30 days' time scale but gradually changed from 30 days onward.

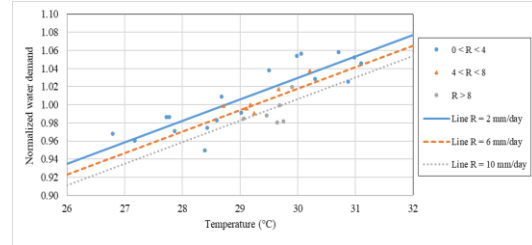
For rainfall, the relationship between a percent change of normalized water demand per mm/day of rainfall and time scale can be expressed with polynomial function with $r^2 = 0.9535$ as follows

$$C_r = 4.0 \times 10^{-5} t^2 - 0.072t - 0.0165$$

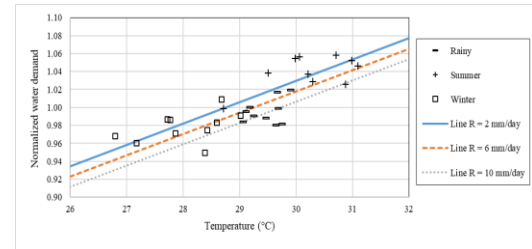
where C_r is a percent change of normalized water demand per mm/day of rainfall and t is also a time

scale in days. From Figure 5(b), the impacts were changed rapidly during 1-60 days' time scale but rarely changed after 60 days' time scale.

From Thailand's second assessment report on climate change (TRF, 2016), the future scenarios of temperatures in each decade from 2011-2100 were

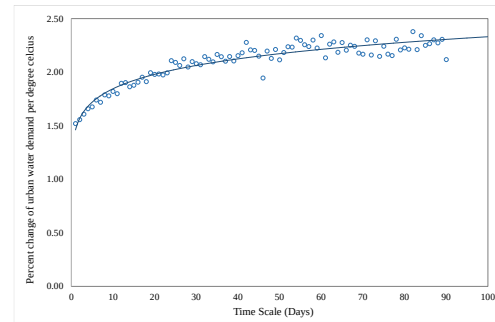


(a) Seasonally time scale normalized water demand.

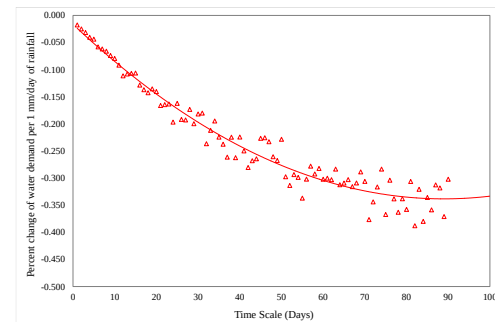


(b) Normalized water demand based on seasons.

Figure 4. Impacts of temperature and rainfall on normalized water demand based on seasonally time scale



(a) Temperature



(b) Rainfall

Figure 5. Percent changes of normalized urban water demand by time scales

estimated based on three climate global models. Since MWA has also forecasted their water demand based mainly on economics factors to be 6.684 MCM/day in 2047, difference temperatures between the decade 2011-2020 and the decade 2041-2050 will be used as temperature increment from climate change. Average temperature increments for RCP4.5, RCP6.0 and RCP8.5 from three models are 0.63°C, 0.33°C and 0.92°C, respectively. Based on our results, these would results in an increment of daily water demand around 96,000, 50,400 and 140,500 m³/day. These numbers will help MWA to prepare for a better plan for their future water supply.

Conclusions

This research presents impacts from temporal scales of two weather variables, temperature and rainfall, on urban water demand of Bangkok and its vicinity areas. Various time scales of data were analysed by using multiple linear regression to find their impacts. Statistical analyzes of urban water demand showed that temperature and rainfall influenced urban water demand for all time scales. Temperature had a stronger positive impact while rainfall had a weak negative impact. As time scale increases, the impact became stronger and followed the power and polynomial form equations for temperature and rainfall, respectively. The magnitudes of temperature impact from daily to weekly, monthly and quarterly time scales were in the order of 1.1-1.6, whereas, the magnitude of rainfall impact is in the order of 3.8-21.8. An average surplus of water supply for short-term water demand is approximately 290,000 m³/day while for mid- to long-term water demand is approximately 4.74 MCM/month.

Temperature increment from climate change in the future will increase MWA daily demand forecast between 50,000-140,500 m³/day in 2047. Therefore, MWA who is responsible for providing potable water in the area should plan for short-term and long-term water demand by including the weather variables in their forecast model.

Acknowledgement

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References

- Adamowski, J. and Karapataki, C. (2010). Comparison of multivariate regression and artificial neural networks for peak urban water demand forecasting: Evaluation of different ANN learning algorithms. *J. Hydrol. Eng.*, 15(10):729-743.
- Arifwidodo, S.D. and Tanaka, T. (2015). The characteristics of urban heat island in Bangkok, Thailand. *Procedia - Social and Behavioral Sciences*, 195:423-428.
- Donkor, E.A., Mazzuchi, T.A., Soyer, R. and Roberson, J.A. (2014). Urban water demand forecasting: Review of methods and models. *J. Water Resour. Plann. Manage.*, 140(2):146-159.
- Goodchild, C. W. (2003). Modelling the impact of climate change on domestic water demand. *Water Environ. J.*, 17(1):8-12.
- Hall, A. (1994). Testing for a unit root in time series with pretest data-based model selection. *J. Bus. Econ. Stat.*, 12:461-470.
- House-Peters, L.A. and Chang, H. (2011). Urban water demand modeling: Review of concepts, methods, and organizing principles. *Water Resour. Res.*, 47(5):15.
- Limsakul, A. and Limjirakan, S. (2012). Trends in Thailand pan evaporation from 1970 to 2007. *Atmos. Res.*, 108:122-127.
- Miaou, S. (1990). A Class of Time Series Urban Water Demand Model with Nonlinear Climatic Effects. *Water Resour. Res.*, 26(2):169-178.
- Minns, A.W. and Hall, M.J. (1996). Artificial Neural Networks as Rainfall-Runoff Models. *Hydro. Sci. J.*, 41(3):399-417.
- Polebitski, A.S. and Palmer, R.N. (2010). Seasonal Residential Water Demand Forecasting for Census Tracts. *J. Water Resour. Plann. Manage.*, 136(1):27-36.
- Said, E.S. and Dickey, D.A. (1984). Testing for unit roots in autoregressive-moving average models of unknown order. *Biometric.*, 71(3):599-607.
- TRF (Thailand Research Fund). (2016). Thailand's second assessment report on climate change 2016, Bangkok, Thailand, 530p.
- Toth, E., Bragalli, C., and Neri, M. (2018). Assessing the significance of tourism and climate on residential water demand: Panel-data analysis and non-linear modelling of monthly consumptions, *Environ. Modell. Software*, 103:2-61.
- United Nations. (2018). World urbanization prospects: The 2018 revision. United Nations. New York. 103p.
- WWAP (United Nations World Water Assessment Programme). (2014). The United Nations world water development report 2014, Vol. 1: Water and Energy. UNESCO CLD, Paris, 230p.