Artificial Groundwater Recharge Field Experiments Evaluation by Time Series in Abu Simbel, Egypt

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Abstract. Artificial recharge of aquifers is one of the applications carried out to benefit from surplus rainwater, surface water, flood water or even treated water. The advantages of artificial charging of groundwater are that it works to recharge the groundwater reservoir to enhance its capabilities of the groundwater reservoir or to improve its quality or to reduce the interference of seawater and benefit from the stored water when needed. Since 2001, Research Institute for Groundwater (RIGW) conducted artificial recharge experiments through open basins and injection well with surface water in Abu Simbel Experimental station, Tushka from a Lake Nasser (LN) were tested in order to monitor the water levels. and improve water quality. The groundwater levels (GWL) monitoring of the aquifer was observed to describe the spatial piezometric and to show the effect of the artificial recharge. Time series (TS) analysis is a useful concept for hydrological variables prediction such as; water consumption, temperature, water levels, and water quality. This study is carried out to simulate GWL by TS analysis for observation network in Abu Simbel, Tushka, Egypt. The overall objective of the paper is to evaluate the GWL trend for GW observation points for (RIGW) experimental station at Tushka, Egypt, and to predict levels of GW using Holt-Winters and ARIMA TS models. In this research, Holt-Winters and ARIMA models were compared for their accuracy. The results indicated that the ARIMA model provided the best prediction.

1. Introduction

Managed aquifer recharge (MAR) is one tool for GW management that can restore over-allocated or brackish aquifers, protect GW-dependent ecosystems, enhance urban and rural water supplies, reduce evaporation losses and improve water supply security.Casanova et al. (2016) carried out (MAR) technologies to increase the available quantities of GW by increasing GW infiltration in to aquifer formations. Some MAR technologies can also be used to overcome saltwater intrusion and surface water pollution by monitoring the geopurification and attenuation processes.

TS modeling is a very important tool for accurate forecasting. It is used to analyze past data or past observations collected at regular time intervals (weekly, monthly, quarterly, or annually) to develop an appropriate model to use for future forecasting. TS models provide extrapolation and prediction for GW data. In GW, or water resources, forecasting future trends depends on available historical data for GWL according to GW monitoring for the previous years. The TS model is used to predict hydrological and environmental variables such as water levels, river floods, temperature, precipitation, and evapotranspiration. TS analysis is conducted for data or observations made at regular time intervals. TS analysis include; 1) describing TS data; 2) model fitting and; 3) forecasting. TS forecasting is used in a lot of fields like the business sector, tourists, industry, unemployment, finance, and hydrogeological sector, and environmental (e.g., water levels, daily rainfall, and air quality). TS is also considered a useful tool for GW prediction. GWL prediction is one of the GW management tools. This prediction is done using several models based on historical data. It is useful to help decision-makers take the necessary actions for GW strategies and GW planning. GWL TS analysis is considered a univariate TS.

The univariate TS models are useful for short time forecasting. Simulation of GWL and trends provide information on GW decline or GW rise.

For simulating GWL, TS models are the most accurate and common models such as, the integrated TS model, the autoregressive moving average model (ARMA), the moving average method (MA), the autoregressive integrated moving average method (ARIMA), Holt-Winters model (HW) and the seasonal autoregressive integrated moving average models (SARIMA). GWL depends on several factors including extraction, aquifer recharge naturally and artificially, aquifer thickness, hydraulic parameters, slope and distances between production wells.

Numerous studies have simulated data using TS analysis in different fields. Heydari et al. (2020) studied the importance of TS in environmental variable prediction. They modeled climate parameters data for predicting, temperature, sunrise hours for 30 years from 1981 to 2010 by Holt-Winters. They indicated that the Holt-Winters model is more efficient for climate parameters forecasting. TS models also are used widely in water consumption simulation. Razali et al. (2018) applied ARIMA and Holt-Winters models to forecast the water consumption at the University of Malaysia from 2006 to 2014. Kozalowski et al. (2018) applied Holt-Winters for modeling hourly water consumption in a water supply system in Pulawy, Poland. The results of the studies show that more investigation and more monitoring are necessary to improve the prediction. TS analysis is applied in some other fields such as, environmental, hydrology, financial, and business. Wasik and Chmielowski (2016) forecasted the amount of sewage inflowing into the wastewater treatment plant in Poland in years 2008–2014 by Holt-Winters method. Hadi and Shokri (2013) indicated that water level forecasting is important in water resource management. For Urmia Lake in Iran, the measurements were used from 1965 to 2011 in simulation.

Also in groundwater, TS was used in numerous studies. Takafuji et al. (2019) used TS models ARIMA and Sequential Gaussian Simulation (SGS) to predict the GW table levels for aquifer in Brazil. The data were collected at 49 wells. Gibrilla et al. (2018) indicated that modeling of future trends of GWL is an important tool for sustainable development and scientific management of GW. Patle et al. (2015) indicated that TS can be used for effective planning for GW utilization. Sakizadeh et al. (2019) applied ARIMA and Holt-Winters models for the simulation of 27 years of GWL records from 1984 to 2012 in the Malayer Plain, Iran. The study was conducted to show the effect of overexploitation of GW on water levels. The study forecasted a decline in GWL in 2022.

Yang et al. (2019) compared three-TS models; (Holt-Winters, integrated TS, and (SARIMA) by applying three models on simulation GWL in a coastal aquifer of south China from 2000 to 2011. They assessed models' performance according to the coefficient of determination; root means square error (RMSE), and the degree of correlation among the observed and predicted values. The results indicated that the SARIMA model is a more reliable capability compared with Holt-Winters, integrated TS model.

There are many modern methods for determining the GWL, such as the machine learning method. (Saeideh et al. 2022) predicted monthly GWL in an unconfined aquifer using; 1) artificial neural network, 2) fuzzy logic, 3) adaptive neuro-fuzzy inference system, 4) group method of data handling, and 5) least-square support vector machine. The methodology assumed that GW dynamics depended on like monthly GWL, precipitation, temperature, and evapotranspiration as hydrogeological and meteorological factors. The study indicated that machine learning method's to simulate the changing in GW water level in a monitoring well.

In this research, the study area in khour_Abu Simbel in Tushka. It is located in the arid region in south of Egypt. It is located adjacent to (LN). Hydrogeologically, the aquifer system in Tushka is composed of sands and sandstone intercalated with clay and basement rocks are appeared at the surface in the south east of khour_Abu Simbel. One of the GW challenges in the region is that the aquifer has limited potential because of the presence of overlapping layers of mud and development depends mainly on surface water.

In this research TS analysis was simulated for weekly data for GW water levels in khour Abu Simbel to provide extrapolation of GWL. As a case study, monthly GWL data collected for 20 years from 2001 to 2020 for 8 monitoring wells in Abu Simbel, Tushka. The overall objective of the research is GWL forecasting to ensure the sustainable use of aquifers. In this study, the performance of Holt-Winters and ARIMA is compared for the prediction of GWL trends over a monitoring period of 20 years in Abu Simbel, Tushka.

The GWL ranged from (165 to 170m) relative to mean sea level. The monthly data of GWL was used from 2001 to 2020. All data were obtained by RIGW team. This research compared three forecasting methods to select the most suitable one for GWL simulation. The three methods match the empirical data and forecasts. Differences between the observation and calculating data on GWL indicated that there exist some additional factors affecting GWL such as GW extraction and GW recharge.
This paper is structured into five sections: 1) A theoretical review and methodology, 2) Hydrogeological characteristics and historical data for GWL in Tushka, 3) TS GW data analysis by (Holt-Winters and ARIMA), 4) Forecasting GWL, and 5) Findings and recommendations. HW, MA, and ARIMA models were applied to forecast the GWL in Abu Simbel from 2001 to 2020. The three models were compared according to MADE: mean absolute percentage error (MAPE) and MAD: mean absolute deviation. The results indicated that the two models are accurate in data simulation but ARIMA is more accurate in prediction. Average rates of water level declining or increasing were 1 to 2 m/yr. The results of forecasting indicated that rising in GWL will be 1.5 to 2.5 m/yr during the next 3 years.

2. Study Area

khour_Abu Simbel is located in Abu Simbel area at the west of (LN). It lies between 22^o 24' 30" to 22^o 26' 00" N and 31^o 36' 40" to 31^o 38' 30" E Fig. 1. It covers about 40 km^2. The land surface ranges from about 170 m to 180 m according to mean sea level (AMSL). It lies in the arid zone and there isn't any rainfall there. In khour_Abu Simbel according to Aswan meteorological station, the maximum daily temperature in summer is 45^o C and the minimum temperature in winter is 9^o C. The daily evapotranspiration ranges from 7 mm/day in winter and 30 mm/day in summer.

According to the geologic map of Egypt (Conoco 1987) and hydrogeological maps (RIGW, 1998 and RIGW 2016) the logs of drilled wells in Tushka the Nubian Sandstone aquifer (NSA) is the main aquifer in khour_Abu Simbel. NSA consists of sand intercalated with clay, silt, and shale. (LN) formation varies in thickness from 40 to 80m. The thickness of Abu Simbel sandstone varies from 110 to 140m.
(LN) was formed after the High Aswan Dam construction in 1960. It is the second-largest artificial lake in Africa. It covers a surface area of 5237 km^2 at a 182m water level and has a storage capacity of 150 – 165 km^3 of water (Van Zwieten et al. 2011). For (LN), there are 85 inlets of side extensions known as khuors. Water levels in (LN) range between 150 to 183m. Its length about 500 km and its width ranges from 3 to 18 km. It runs about 350 km in Egypt and about 150 km in Sudan.

Figure. 1. Location of khour_Abu Simbel

3. Experimental Work

Abu Simbel experimental station was constructed at 1998 by Ministry of Water Resources and Irrigation, Egypt. The research experiment station depends on monitoring the change in GWL as a result of the research experiments that took place in the period from 2001 to 2019. The test station Fig. (3 and 4) consists of a combination of different underground recharging techniques. First, the surface recharging technique, through a surface basin with dimensions of 190 x 107 and a depth of 9.5 m, through which surface recharging experiments are carried out through leakage from the base and the sides of the basin or through nine of gravity wells; Second, the injection through deep injection well with depth 250m.

In the last 20 years, (RIGW) conducted 20 experiments by infiltrate water through recharge basins. Experiments were conducted by filling the basin from 0.7m to 3.0m according to the available surface water. The duration of the infiltration was from 20 to 50 days. A monitoring program is executed for observing the changing and fluctuation of GWL through monitoring network of 25 wells with different depths range between 50 to 200m. During the experiments, the fluctuation of water levels, the supplied water flow rate, and the evaporation rate were measured.

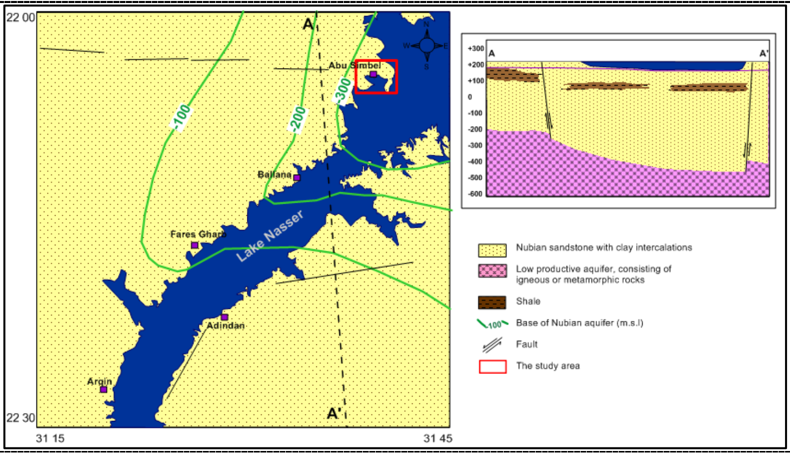

Figure. 2. Aquifer system of Tushka (RIGW 1998 and RIGW 2016)

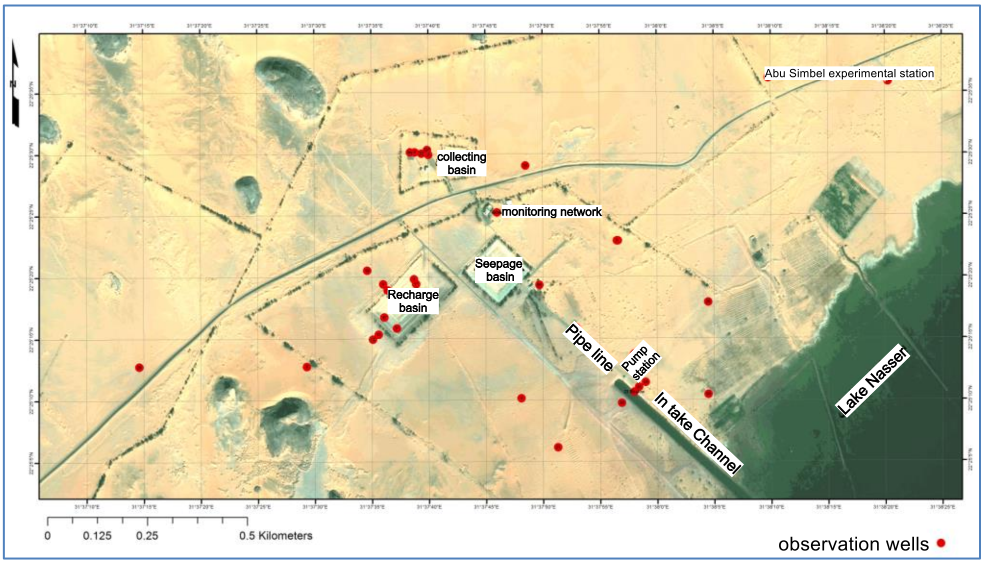

Figure. 3. Layout of Abu Simbel Experimental station, b) Recharging field experiments

Field investigations by RIGW team were conducted to study the change in water levels of (LN) monthly from 2001 to 2020. The lowest water level was recorded at 168.2 in June 2012. The highest water level was recorded 180.96 in November 2019 Fig. (4).

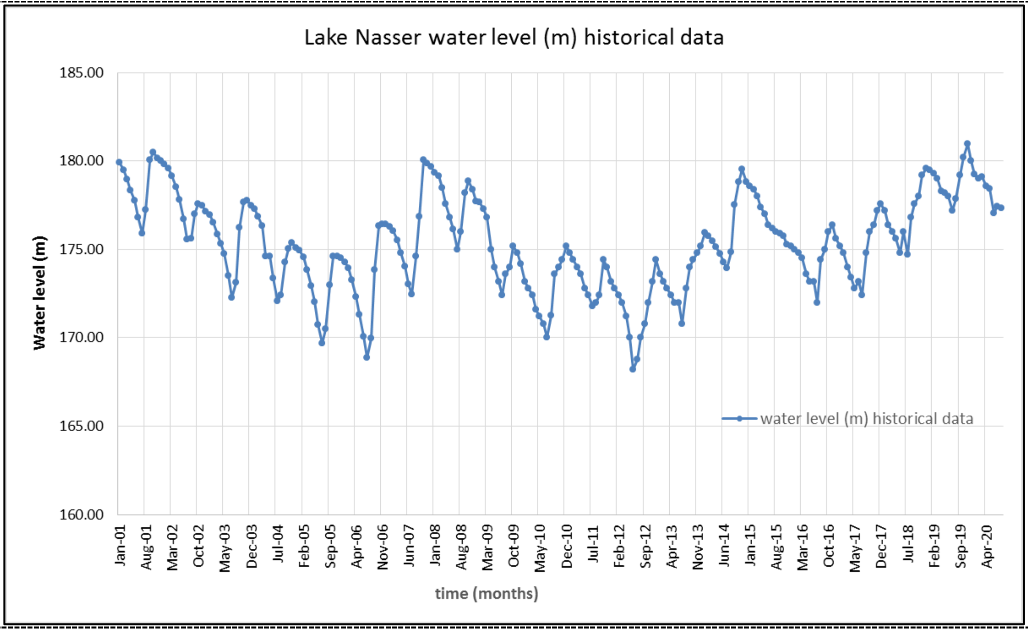

Figure. 4. (LN) water level (m) relative to mean sea level

4. Time Series Analysis

TS analysis for GWL is very useful for detecting trends, GW behavior, effective planning for sustainable GW development and GWL forecasting. In this paper TS was simulated for weekly data for GWL in khour Abu Simbel in Tushka for 20 years from 2001 to 2020 for 8 monitoring wells in Abu Simbel Tushka by two models (Holt-Winters and ARIMA).

4.1. Holt-Winters (HW)

Holt-Winters is the most widely model used for simulation and forecasting (Hot 1957). It deals with a linear trend component, seasonal variation component, and a random component. HW method is based on exponential smoothing. It uses for variable simulation then it uses for prediction (Eqs. 1-5).

$$L_t = \propto \left(\frac{Y_t}{S_{t-M}}\right) + (1-\propto)(L_{t-1} + T_{t-1}) \quad (1)$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \quad (2)$$

$$S_t = \gamma\left(\frac{Y_t}{L_t}\right) + (1-\gamma)S_{t-M} \quad (3)$$

$$F_{t+k} = (L_t + k * T_t) * S_{t-M+k} \quad (4)$$

$$y'_t = (L_{t-1} + T_{t-1})S_{t-p} \quad (5)$$

Where α, β, γ smoothing parameters are chosen between 0 and 1. To determine the best smoothing parameters, the mean average errors must be minimizing. L_t is level at time t. T_t is the trend at time t and S_t is the seasonal component at time t. y'_t is the fitted value at time t.

4.2. ARIMA

The (ARIMA) model (Box and Jenkins 1976) was used for TS modeling for GWL. ARIMA model is TS data model. It includes 3 parts; 1) Autoregressive (AR), 2) Integrated, and 3) (MA) which are expressed as ARIMA (p, d, q) where:

- P: autoregressive part
- d: integrated part (differencing)
- q: MA part

In this research GWL represented by y_t, it is expressed by Eq. (6):

$$Y_t = y_1 + y_2 + y_3 + \cdots + y_t \quad (6)$$

Where y_1, y_2, y_3,…. Are the observation at time t_1, t_2,t_3,….

The autoregressive part (AR): it explains the relationship between present and previous P observations (Eq. 7).

$\mathrm{Y_t} = \emptyset_0 + \emptyset_1 \mathrm{y_{t-1}} + \emptyset_2 \mathrm{y_{t-2}} + \cdots + \emptyset_\mathrm{p} \mathrm{y_{t-p}} + \varepsilon_\mathrm{t}$ (7)

Where Φ_o is constant, Φ_1, Φ_2, Φ_3, …., Φ_p: autoregressive coefficients, P is order of autoregressive model and εt is random error.

If P=1, It means that each observation is a function of only one previous observation (Eq. 8)

$\mathrm{Y_t} = \emptyset_0 + \emptyset_1 \mathrm{y_{t-1}} + \varepsilon_\mathrm{t}$ (8)

(MA) part explains the relationship between observation and previous q errors. If q=1, it means that each observation is a function of only one previous error (Eq. 9).

$Y_t = \theta_0 + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t$ (9)

Where θo is constant, θ1, θ2, θ3, …., θq: MA coefficients, q is the order of MA.

Integrated (I): represents the observed values are modeled directly or differences between consecutive observations are modeled. If d=0 it means that the series is modeled directly.

So ARIMA model at p,d,q can be written Eq. (10)

$Y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}$ (10)

Where, Y_t is GWL at time t, P is the order of autoregressive model, d is the number of times that differences, q is the order of MA, c is the constant value, Φ_1, Φ_p is the parameter of autoregressive, θ_1, θ_p is the parameter of MA, ε_t is the error at time t.

ARIMA model consists of four steps (Gibrilla et al. 2018) and (Patle et al. 2015): 1) Preparing of data and data differencing, 2) Model identification by the behavior of autocorrelation function (ACF) and partial autocorrelation function (PACF), 3) Choosing the model parameters (p,d,q), 4) Diagnostic testing stage to check the model assumption and check the accuracy of the fitted model and 5) Forecasting stage.

5. Results

To study the trend and fluctuations of GWL in khour_Abu Simbel, the records from a ten observation wells between 2001 and 2020 were investigated, Fig. (5) shows the records of GWL. The curves show that the GWL variability is the highest during the flood period (September – February). w8, w10, w11, w13, w1, and w5 during 20 years increasing in GWL are about 8m which is equal to increasing 0.4m annually. W22' and w22" during 20 years increasing in GWL is about 2.6m which is equal to increasing 0.13m annually. In this study, the multiplicative model for HW model is applied for simulation and forecasting for the eight piezometers. The model was developed by Excel to solve the model equations. Firstly seasonal component St and level time Lt and trend Tt at time t were calculated monthly from January 2001 to August 2020. Errors between the calculated and estimated values were calculated. Solver tool in Excel was used to estimate the optimum smoothing parameters α, β, γ for the minimum error. The smoothing parameters were calculated α = 0.83 to 0.99, β = 0.02 to 0.03 and γ = 1.0.

- The value of calculated α indicated that the GWL resulting from the forecast are highly dependent on the most recent GWL in historical observations.
- The value of calculated β indicated that the initial value is constant.
- The value of calculated α indicated that the seasonal values depend on the most recent GWL in historical observations.

Fig. (6a) shows 8 curves for eight observation wells for the fitted values of estimated GWL by Holt-Winters model from 2001 to 2020. Model accuracy parameters; (MAPE), (RMSE), and R squared (R^2) were calculated in table (1).

Table 1. Model accuracy parameters for Holt-Winters model

Parameter	W8	W10	W11	W13	W22'	W22"	W1	W5
MAPE	0.067	0.709	0.65	0.68	0.466	0.5266	0.14	0.138
RMSE	0.166	0.1729	0.238	0.17	0.43	0.37	0.38	0.368
R^2	0.9922	0.9926	0.993	0.991	0.939	0.944	0.988	0.991

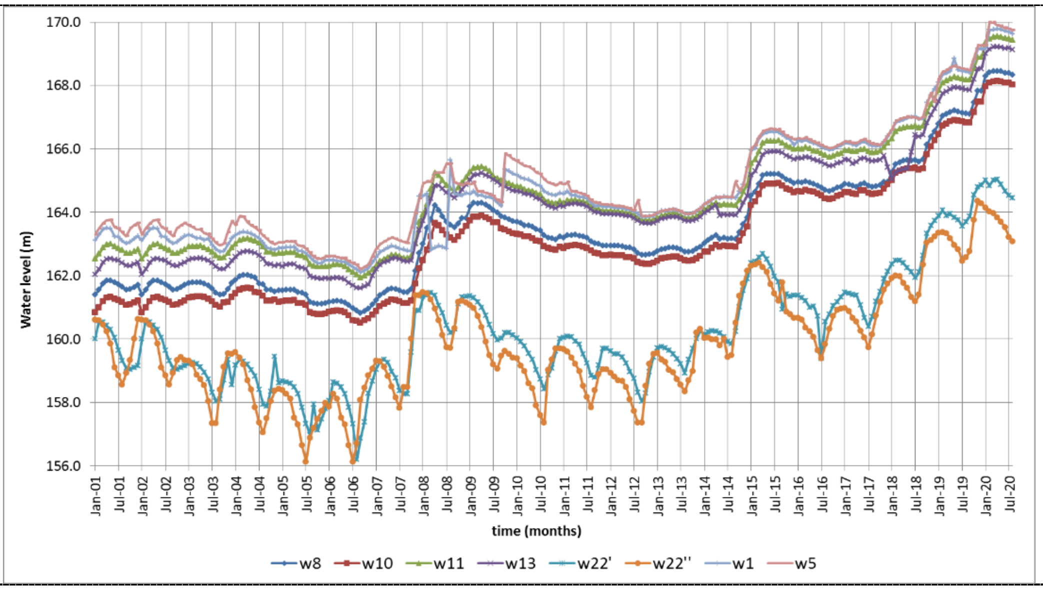

Figure. 5. GWL during the period 2001 to 2020 (m) relative to mean sea level

SPSS 17.0 software was used for ARIMA modeling of TS data. GWL data for eight observations from 2001 to 2020 was used for identification of models and validation and testing of model accuracy according to Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R squared Error (R^2). Then the best ARIMA model was used for GWL forecasting.

For the eight observations some models were applied; (1,1,1), (2,1,1), (6,1,6), (2,1,2), (9,1,9) for w8, w10, w11, and w13, (1,1,1), (2,1,1), (6,1,6), (2,1,2), (12,1,12) for w22', (1,1,1), (2,1,1), (5,1,5), (8,1,8), (12,1,12), (13,1,13) for w22", (1,1,1), (2,1,1), (5,1,5), (14,1,14) for w1 and (1,1,1), (2,1,1), (3,1,3), (5,1,5), (13,1,13) for w5 respectively. For all models plots of autocorrelation function (ACF) and partial autocorrelation function (PACF) were plotted for 25 models to select the best models in Fig. (7) for example for well No 8.

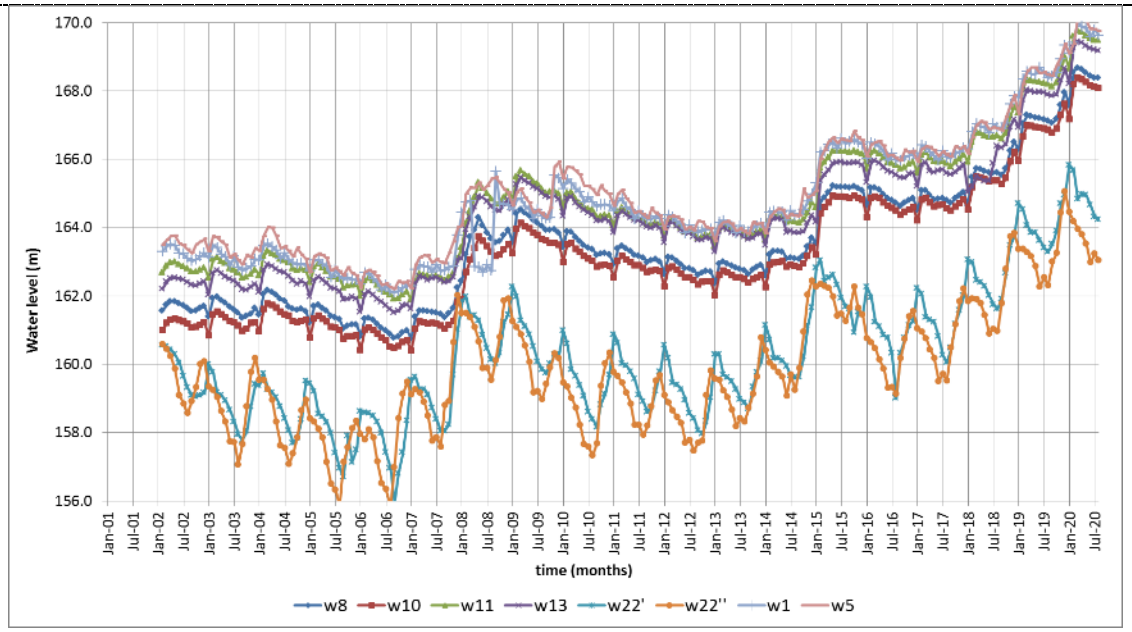

Figure. 6. a). GWL Holt-Winters

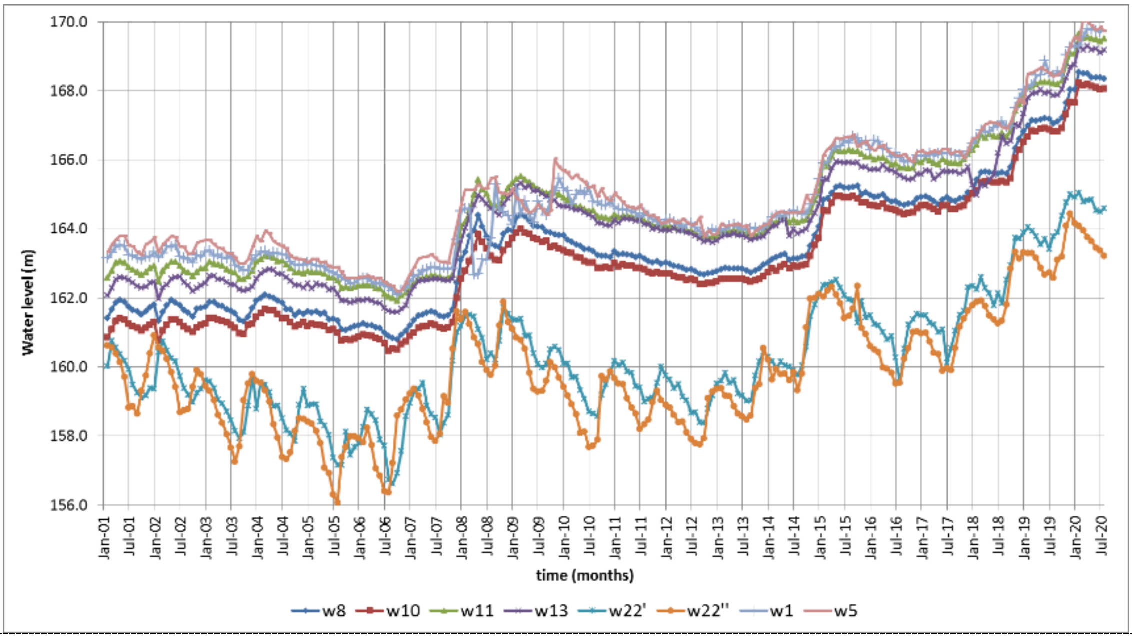

Figure. 6. b). GWL ARIMA

According to ACF and PACF, the best models for w8, w10, w11, w13, w22', w22'', w1 and w5 are (9,1,9), (9,1,9), (9,1,9), (9,1,9), (12,1,12), (12,1,12), (14,1,14) and (13,1,13) respectively. Fig. (6b) shows 8 curves for eight observation wells for the fitted values of estimated GWL by ARIMA model from 2001 to 2020. Model accuracy parameters; (MAPE), (RMSE), and R squared (R^2) were calculated in Table 2.

Holt-Winters and ARIMA models were applied to GWL simulation. According to table (1 and 2) ARIMA is better than Holt-Winters and numerical based on (MAPE), (RMSE) and (R^2)values. The results of the curves indicate the quality of the common trend in the results and the quality of the seasonal maximum and minimum peaks. RMSE for Holt-Winters and ARIMA models range between (0.939 to 0.998) that considered a good indicator.

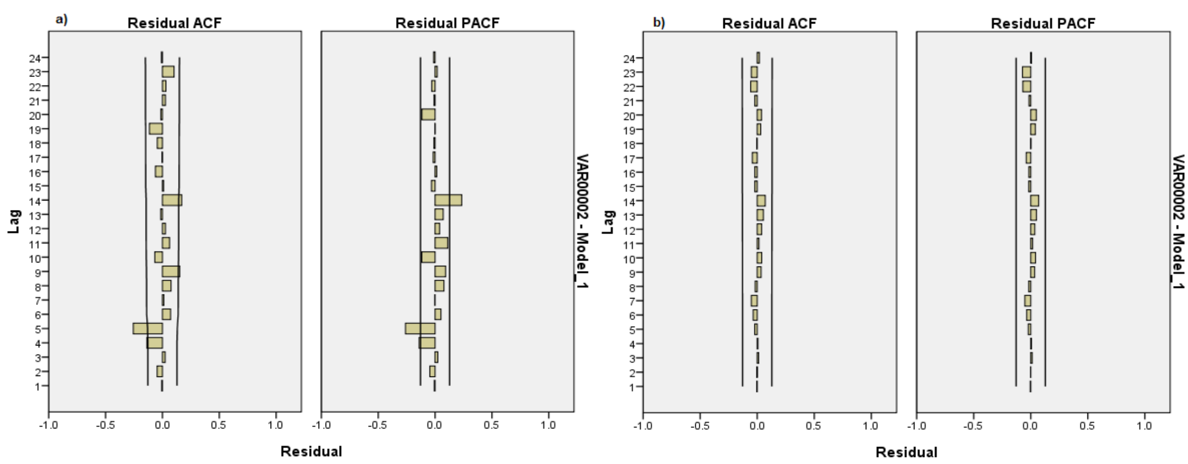

Figure. 7. ACF and PACF a) (1,1,1) model and b) the best model (9,1,9) for W8

Table 2. Model accuracy parameters for ARIMA model

Parameter	W8	W10	W11	W13	W22'	W22"	W1	W5
MAPE	0.039	0.037	0.036	0.045	0.12	0.119	0.075	0.068
RMSE	0.102	0.1	0.097	0.112	0.29	0.295	0.277	0.186
R^2	0.997	0.998	0.998	0.997	0.977	0.975	0.979	0.991

According to the results of the two models Holt-Winters and ARIMA, the ARIMA model was selected as the best model for GWL simulation in Khour Abu Simbel. So it is used for forecasting GWL in eight wells for the next three years (2021 to 2023) for the eight wells in Fig. (8). The forecasting doesn't consider climate change or increased GW pumping, artificial recharge.

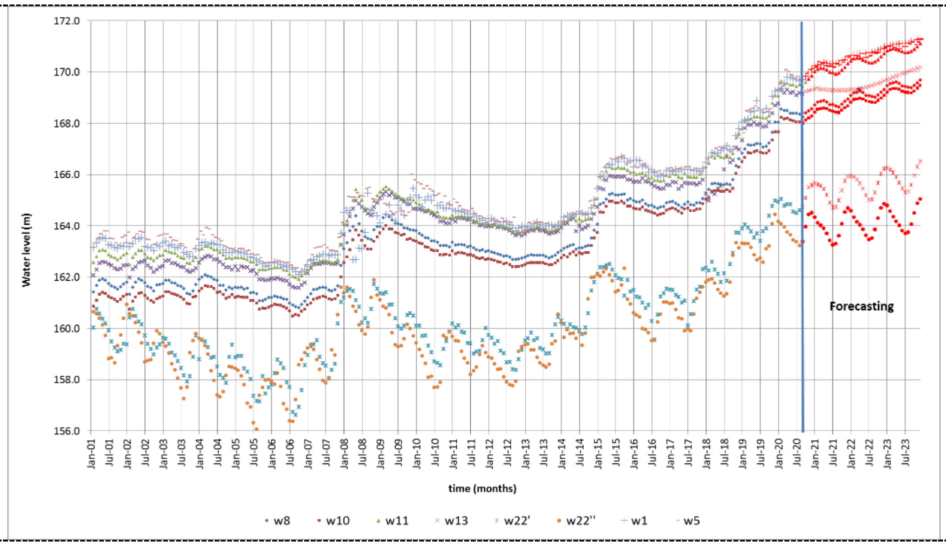

Figure. 8. GW forecasted levels ARIMA

6. Conclusions

TS analysis has been widely used in recent years in environment, hydrology, water resources and GW fields. This paper methodology depends on applying two-TS models Holt-Winters and ARIMA model and test their accuracy and their potential for simulation and forecasting GWL in Khour Abu Simbel, Tushka as a case study. khour_Abu Simbel is located in Tushka in South Egypt in (NSA). In khour_Abu Simbel there is monitoring network for measuring GWL with time. The monitored long term observation monthly GWL data series from 2001 to 2020 used in simulation and prediction.

The accuracy of models was evaluated with (MAPE), (RMSE), and R squared (R^2). The results indicated Holt-Winters and ARIMA models had applicable accuracy. ARIMA model is more accurate and more sophisticated for forecasting.

According to the analysis the results show the most suitable models for each well (w8, w10, w11, w13, w22', w22", w1 and w5). In kour Abu Simbel, Tushka and according to data trend, long term GW fluctuation trends indicate the effect of GW recharge artificially and naturally by (LN).

According to the research findings, and as for the nature of the area, future studies must be made about the change in GWL in the area over time, and the relationship between the area's GW and surface water represented by (LN). The study recommended continuous monitoring in observation wells and the need for (LN) water levels.

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