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Forecasting of Monthly Closing Water Level of Angat Dam in the Philippines: SARIMA Modeling Approach

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ABSTRACT

The operation and management of Angat Dam as a multipurpose dam for domestic, irrigation, power, and flood control purposes, is governed by the operation rule curve of dam water level. This study was conducted to understand the behavioral pattern and to provide short-term forecast of the monthly closing water level of Angat Dam using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, considering the data from January 1990 to December 2021. Series decomposition revealed the absence of an overall trend component but the presence of seasonality in the dataset. An almost perfect partial correlation between the closing water level of a certain month and the preceding two months' records was observed in the correlogram. Different SARIMA models were evaluated and subjected to diagnostic checking and based on minimum Akaike Information and Bayesian Information criteria, SARIMA (1,0,1) (0,1,1)12 model with estimated coefficients of $\varphi_1 = 0.8050$, $\theta1 = 0.2278$, *and* $\Theta_1 = -0.999$ *was selected to forecast the monthly closing water level of Angat Dam. The model fits with a root mean square error (RMSE) of 4.79 meters, mean absolute error (MAE) of 3.45 meters and coefficient of determination* (R_2) *of 0.93. On average, the forecast water levels of the best SARIMA model are off by around 1.8% of the actual value.*

Keywords: *SARIMA, autocorrelation, forecasting, Angat Dam, invertibility, stationary*

INTRODUCTION

As water demand increases, the availability of freshwater is likely to decrease. This demand originates from agriculture, energy production, industrial uses, and human consumption (*UNESCO - WWAP 2021*). In some developing, and highly populated countries, a decrease availability was apparent. The Philippines, particularly Metro Manila which is the most congested Asian city, has been experiencing water shortage (*Laforga 2019*).

The Angat Dam, a multi-purpose reservoir completed in 1967 in Norzagaray, Bulacan, Philippines, is the primary source of water for Metro Manila. It supplies 935 million gallons of water per day to water-deficient areas which include Metro Manila and 18 municipalities within the Metropolitan Waterworks and Sewerage System franchise area (*MWSS 2012*). The water from Angat Dam is distributed by Manila Water (east zone) and Maynilad (west zone) which accounts for more than 90% of Metro Manila's water supply (*Tansengco-Schapero et al. 2013; Ibañez et al. 2022*). It also provides water to the actual irrigated area of about 17,500 ha and 24,000 ha during the wet and dry cropping seasons, respectively (*Tabios and De Leon 2020*). Moreover, the dam helps minimize flood destruction and generates 246,000 kilowatt electricity required for the Luzon Grid consumption (*DOE 2023*).

Angat Dam has a normal high water level (NHWL) of 210 m during the flood season (May 1 to October 31) and 212 m during non-seasonal flood season (December 1 to April 30) (*NWRB 2009*). The dam operating zone is bounded by the NHWL and the minimum operating level or critical level which is set at 180 m. The reservoir's water level shall not be allowed to fall into critical level or the drought zone, except during critical water shortage periods, where water releases shall be provided in the following order of priority: municipal use, irrigation use, and river maintenance (*NWRB 2009*). In the first quarter of 2019, roughly 12 million people were affected by the water crisis in Metro Manila which was associated with a continuous decrease of the water level of Angat Dam (*Sabillo 2019*). In June 30, 2019, the water level in Angat Dam was at 159.54 m which was 20.46 m below its minimum operating level. Intermittent rainfall did not cause significant rise in the water level of Angat Dam due to the presence of a weak El Niño in the tropical Pacific (*DOST-PAGASA 2019; Tejada et al. 2023*). This continuous decrease in the water level of Angat Dam implied a decrease in water allocations for irrigation and agriculture to prioritize other purposes such as domestic and industrial sectors (*Rola and Elazegui 2008; Jaranilla-Sanchez et al. 2013; Torio et al. 2019*).

This critical situation of the Angat Dam water level can be explored by a modeling procedure such as time series analysis which has a wide range of applications in hydrological studies. Time series analysis is used to detect and describe quantitatively the underlying stochastic processes in given observations, build mathematical models used to generate synthetic hydrologic records, forecast hydrologic events, detect trends and shifts in hydrologic records, and fill in missing data and extend records (*Machiwal and Jha 2006*). Time series of historical records of a single hydrological parameter may use the univariate Box–Jenkins method like the seasonal autoregressive integrated moving average (SARIMA) to predict the coming observations without looking for the time series of other variables (*Adhikary and Gupta 2012; Tadesse and Dinka 2017; Gharde 2016*). Many studies in the field of hydrology utilized SARIMA for short-term forecasting of river streamflow (*Tadesse and Dinka 2017; Moeeni et al. 2017; Abudu et al. 2010; Adnan et al. 2020; Tarakanov et al. 2022*), and rainfall (*Wang et al. 2013; Chang et al. 2012; Kokilavani et al. 2020*), with only a few focusing its application on the water level of natural or man-made reservoir. In the previous years, the potential of SARIMA in forecasting water level was explored at Lake Malawi in East Africa (*Mulumpwa et al. 2018*), and Lake Urmia in Northwestern Iran (*Fathian et al. 2016*).

In the case of Angat Dam, there were already existing studies that intended to provide forecasts of using time series models. One of those was done by *Tabios* (*2008*) who developed an appropriate SARIMA model with SAR(1) and SAR(2) parameters. *Tabios'* (*2008*), however, focused only on using inflow with 6-month forecasting horizon. The forecasted inflow was then incorporated as an input in the optimization-simulation runs of Angat Dam. Moreover, in a recent study by *Ibañez et al.* (*2022*), an ARIMA model was developed to forecast Angat Dam water level at a different forecasting horizon.

Although there had been studies related to forecasting of Angat Dam parameters, this study was conducted to understand the behavioral pattern and to forecast the monthly closing water level of Angat Dam. Closing water was considered in the study because it has been used as indicator variable or the basis for crafting the short-term dam management of Angat Dam including the water allocation for irrigation and domestic use. Specifically, it can contribute to studying the feasibility of using a single parameter in the feasibility of management despite being multi-sectoral of Angat Dam. Hence, this study considered components of historical closing water level data to explain underlying behavioral pattern. It used SARIMA Model for short-term forecasts of the monthly closing water level of Angat Dam.

MATERIALS AND METHODS

The recommended methodology for SARIMA model development and evaluation by *Box and Jenkins* (*1976*) was adopted in this study (**Figure 1**).

The SARIMA is based on stochastic theory considering the serial autocorrelation among the realizations to identify an appropriate statistical model to for the process (*Valipour 2015*). The fitting of the model includes identification, estimation, and diagnostic analysis. SARIMA (p,d,q)(P,D,Q) was defined using lag operator B as:

$$\varphi_p(B)\Phi_P(B^s)(1\text{-}B^s)Z_t = \theta_q(B)\Theta_Q(B^s)a_t \quad (1)$$

where φ(B) and θ(B) are polynomials of order p and q, respectively; Φ(Bs) and Θ(Bs) are polynomials of degrees P and Q, respectively; p (or AR) is the order of non-seasonal auto-regression; d is the number of regular differences; q (or MA) is the order of nonseasonal moving average; P (or SAR) is the order of seasonal autoregression; D is the number of seasonal differences; Q (or SMA) is the order of seasonal moving average; and S is the length of season. In this study, Z_t stands for the monthly closing water level of Angat Dam. All statistical calculations and analysis were done using R software packages like forecast (*Hyndman et al. 2022*) for fitting of candidate best SARIMA models and tseries (*Trapletti and Hornik 2022*) for conducting stationary test and tests on residuals. The significance level for all conducted statistical procedures was set to 5%.

Data Preparation and Model Development

The water level record of Angat Dam from January 1990 to December 2021 was acquired from the National Water Resources Board (NWRB). For model development, the water level data obtained on the last day of every month were utilized. The components of the time series data which include secular trends, seasonal variation, cyclical fluctuations, and irregular movements were dissected to analyze and explain their underlying behavioral pattern. The Mann Kendall trend test (*Kendall 1955; Mann 1945*) and the linear trend test was applied for trend detection on the data.

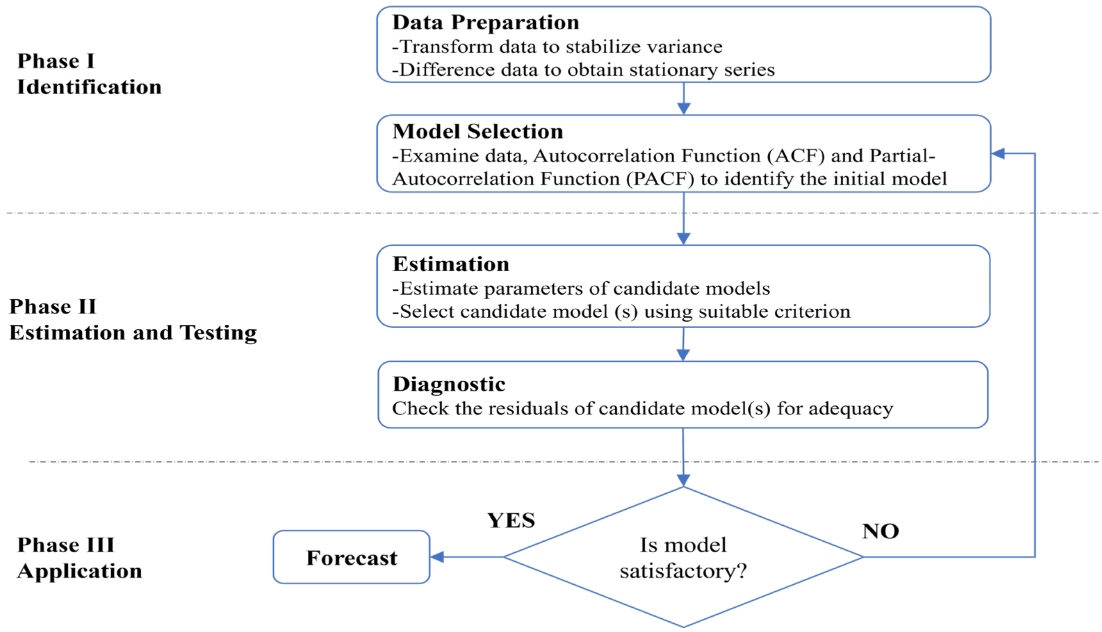

Figure 1. Methodology Framework of SARIMA Model used in this study for forecasting Angat Dam Water Level. Adopted from *Box and Jenkins* (*1976*).

Model Identification and Parameter Estimation

To satisfy the requirement of SARIMA, the series was examined for stationarity by examining an Autocorrelation Function (ACF) plot, and conducting Augmented Dickey Fuller (ADF) Test for Stationarity *(Dickey and Fuller 1979*), Philips-Perron (PP) Test (*Phillips and Perron 1988*) and Kwiatkowski-Philips-Schmidt-Shin (KPSS) Test (*Kwiatkowski and Phillips 1992*). Necessary differencing was done to transform the data into a stationary series and remove the presence of seasonality.

The identification of the candidates and ordering of the model were based on the observed significant spikes in ACF and Partial Autocorrelation Function (PACF) of the stationary series. From the identified initial model, necessary underfitting and overfitting of orders were considered to name the candidate models for diagnostic checking and performance evaluation. The selection of candidate models was based on the satisfaction of invertibility property of the model and the significance of the estimated parameters.

Diagnostic Checking, Measure of Fit

In determining the statistical adequacy of candidate models, a diagnostic checking through residual analysis was done. The residuals were checked if these were uncorrelated or independent each other using the Ljung-Box Test Plot (*Jung 1978*), have zero mean using t-test, have constant variance using ARCH Engle's Test For Residual Heteroscedasticity (*Engle 1982*), and followed normal distribution using Jarque-Bera Test (*Jarque 1980*). To determine the best fitted model, measures of fit namely Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were computed.

$$\boldsymbol{e_t = Z_t - \hat{Z}_t} \tag{2}$$

$$\boldsymbol{AIC = e_t^{\left(\frac{2k}{n}\right)} \left(\frac{\sum_{t=1}^{n} e_t^2}{n}\right)} \tag{3}$$

$$\boldsymbol{BIC = n^{\left(\frac{k}{n}\right)} \left(\frac{\sum_{t=1}^{n} e_t^2}{n}\right)} \tag{4}$$

Where Z_t is the actual water level at time t, $\hat{Z}_t$ is the forecast water level at time t, e_t is the forecast error or residuals at time t, k is the number of estimable parameters, and n is the number of observation points.

Model Evaluation and Forecasting

The evaluation of the performance of the selected best model was done through out-sample validation i.e., refitting the model by withholding the recent 10% of the time series data (January 1990 to December 2017). The consistency of the model for forecasting was checked with acceptable change in the values of estimated parameters between the model development set and model evaluation set. The model's accuracies are evaluated through coefficient of determination (R2), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAE), and Nash–

Sutcliffe ¬Efficiency (NSE):

$$R^2 = \left(\frac{\sum_{t=1}^{n}(Z_t - \bar{Z}_t)(\hat{Z}_t - \bar{\hat{Z}}_t)}{\sqrt{\sum_{t=1}^{n}(Z_t - \bar{Z}_t)^2 \; x \; \sum_{t=1}^{n}(\hat{Z}_t - \bar{\hat{Z}}_t)^2}} \right)^2 \quad (5)$$

$$RMSE = \sqrt{\left(\frac{\sum_{t=1}^{n} e_t^2}{n}\right)} \quad (6)$$

$$MAE = \frac{\sum_{t=1}^{n}|e_t|}{n} \quad (7)$$

$$MAPE = \frac{\sum_{t=1}^{n}|e_t/Z_t|}{n} * 100 \quad (8)$$

$$NSE = 1 - \left(\frac{\sum_{t=1}^{n} {e_t}^2}{\sum_{t=1}^{n}(Z_t - \bar{Z}_t)^2}\right) \quad (9)$$

Where $\dot{Z}_t$ and $\hat{Z}_t$ is the mean of the actual and fitted water level until time t, respectively. Twelve-month horizon of model forecasts from January 2021 to December 2021 were assessed using the best SARIMA model. The performance of the model for dynamic forecasting whichis based on real-time updating of monthly data on a rolling basis, was also evaluated with three-month forecasts horizon.

RESULTS AND DISCUSSIONS

The top image illustrates the time series plot of Angat Dam's water level from January 1990 to December 2020 (**Figure 2**). Focusing on the last decade, the lowest recorded monthly closing water level was 158.74 m in June 2019, and the highest recorded water level was 214.37 m on January 2017. The graph shows seasonality in the data with January as the peak and June as the trough. This indicated that in every January of each year, there was a high water level which decreased on the onset of the summer season. After reaching its lowest point in July, it began to rise again in September, near the end of flood season. On years 2010, 2014, 2015, 2019, the water level was observed below the minimum operating level of the dam for more than three consecutive months, coinciding with the past meteorological drought events in the Angat watershed (*Tejada et al 2023*).

To further investigate the behavior of the data series, its components were dissected with the plot on the seasonality of the data as apparent every year (**Figure 2**). Mann-Kendall trend test (p-value = 0.9873) and linear trend test (y = 0.00135x + 196.5, p-value = 0.8350) indicate the absence of overall trend in the given data which supplemented the graph of the trend component. The remainder component indicates the presence of irregular fluctuations in the water level data through the years.

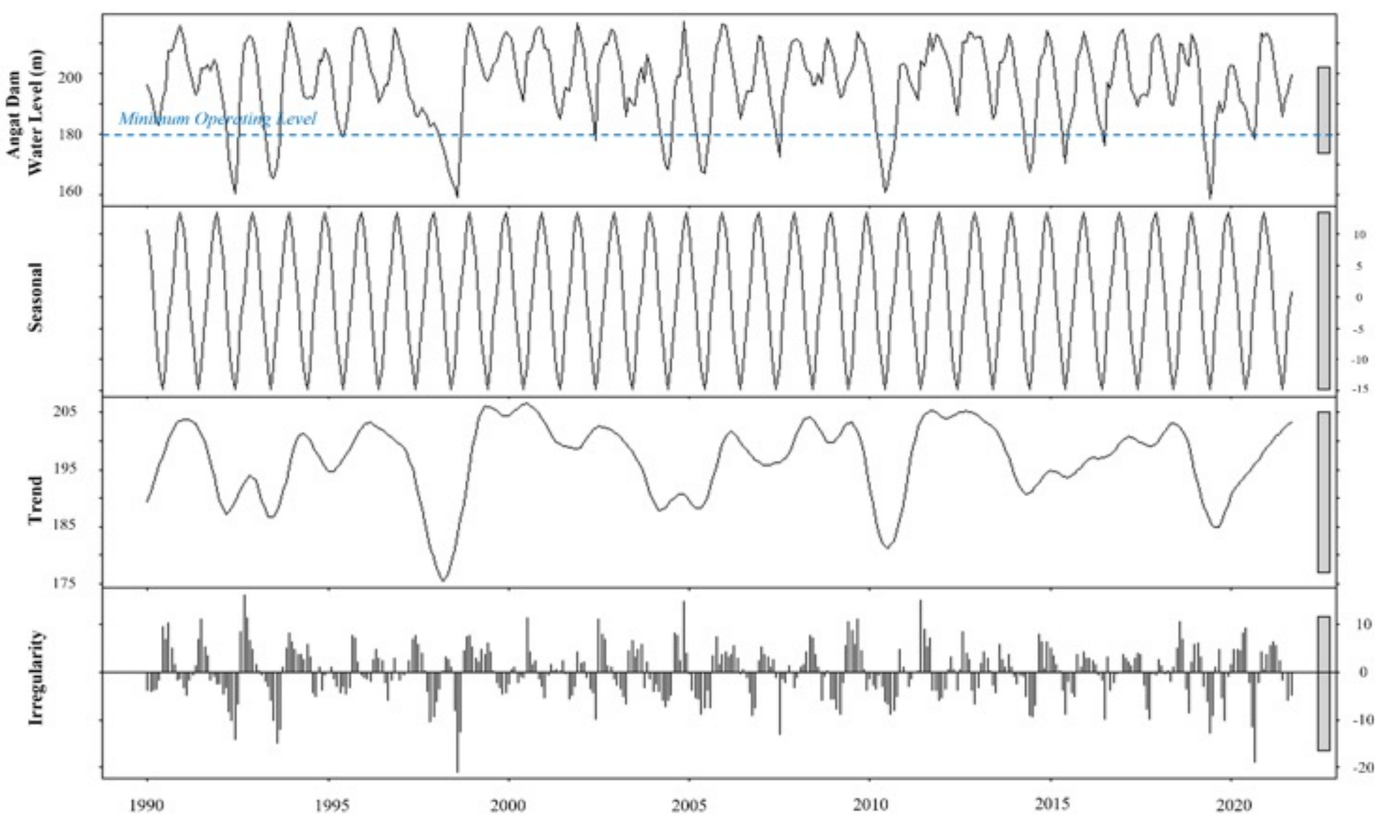

Figure 2. Monthly closing water level (in meters) of Angat Dam from January 1990 to December 2020 (top image) and its seasonal trend, and irregular components.

Models Identification and Parameter Estimation

The computed p-value for ADF, PP and KPSS test of the original series indicates the stationarity at 5% level of significance (**Table 1**).

The ACF correlogram of the original series shows the presence of significant spikes observed at intervals of every 12 months (12th, 24th, 36th lags, ….) (**Figure 3**). These spikes revealed that observed monthly flow series was seasonally non stationary; hence, a seasonal differencing (D=12 or lag 12) was done. The seasonally differenced series (D=12) was determined to be stationary based on the results of test statistics (**Table 1**).

In the ACF correlogram, there were relatively long spikes indicating that there were existing autocorrelations among monthly closing water levels (**Figure 4**). This is understood since the current water level is simply the accumulated water level that depends on the waterlevels of the previous months. Moreover, the PACF correlogram showed that the first and second spikes were relatively long indicating an almost perfect partial correlation between a certain month's closing waterlevel with that of the preceding two months' closing water level. In addition, the 13th spike was also long, indicating a relatively high partial correlation between the closing water level of a certain month and that of the same month of the previous year. For instance, closing the water level for January is highly influenced by the closing water level of January in the previous year. This then indicates that there was seasonality in the series.

Therefore, the initial model is SARIMA (1,0,1) $(1,1,1)_{12}$. Upon overfitting and underfitting the parameters by unity, only three models were identified to be invertible and had a significant value of parameters based on Z-test of coefficients (**Table 2**). Model 1 SARIMA (0,1,0) $(1,1,0)_{12}$, Model 2 SARIMA (1,0,1) $(0,1,1)_{12}$, and Model 3 SARIMA (1,0,0) $(0,1,1)_{12}$.

Diagnostic Checking and Measure of Fit

Only Model 2: SARIMA (1,0,1) $(0,1,1)_{12}$ satisfied the assumptions on mean residuals equal to zero, have constant variance and independence with each other (**Table 3**). The non-normality of the residuals of Model 2 should not affect the evaluation of the forecasting capabilities of the SARIMA model because this was not intended to draw any inference about the coefficients or compute confidence intervals (*Hyndman and Athanasopoulos 2013*). Model 2 also obtained the lowest AIC and BIC that indicating its appropriateness to forecast the closing monthly water level of Angat Dam among the candidate models. The diagnostic check done for SARIMA (1,0,1) $(0,1,1)_{12}$ which suggested that the residuals indeed

Table 1. Computed p-value on the stationary test for the original and differenced data sets (significance level sets as 5%) for the Angat Dam monthly closing water level.

Dataset	*ADF*		*PP*		*KPSS*	
	Test Stat	**p-value**	**Test Stat**	**p-value**	**Test Stat**	**p-value**
Original Data	-6.8966	<0.01	-90.0746	<0.01	0.0339	>0.1
Seasonally Differenced Data (lag 12)	-6.8966	<0.01	-61.7809	<0.01	0.0211	>0.1

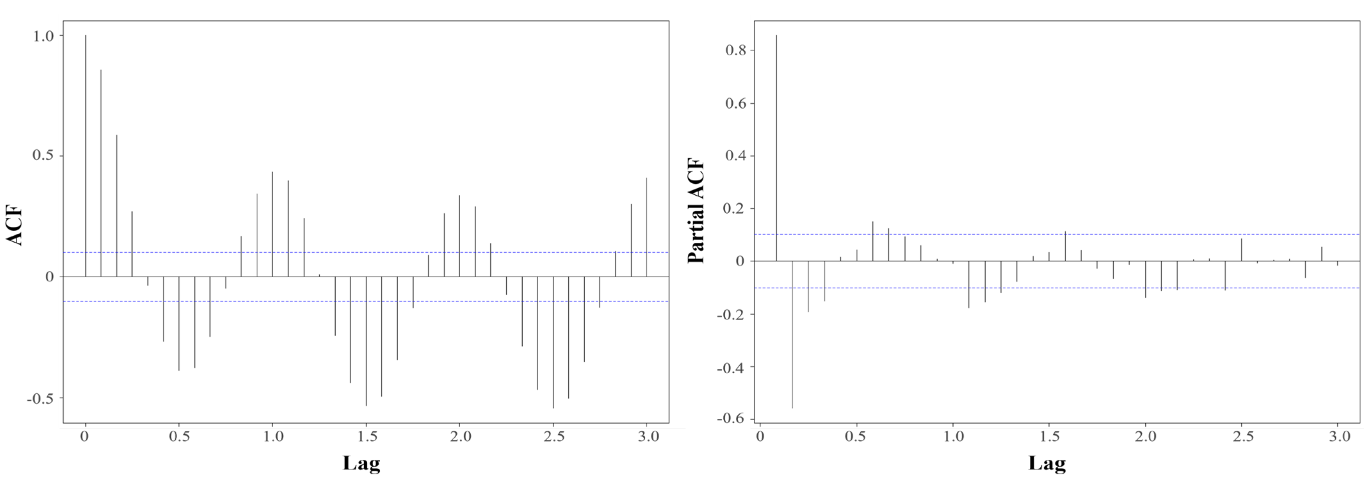

Figure 3. Observed Angat Dam monthly closing water level from January 1990 to December 2020: (Right) correlogram of the estimated autocorrelation function (ACF) coefficients and (Left) estimated partial autocorrelation function (PACF) coefficients.

Table 2. Parameter estimates of candidate SARIMA Models (significance level at 5%).

	Model	Parameter	Estimated Coefficient	Z-value (p-value)
1	SARIMA (1,0,0) $(1,1,0)_{12}$	AR (1) φ_1 SAR (1) Φ_1	0.8728 -0.4935	34.218 (<0.01) -10.377 (<0.01)
2	SARIMA (1,0,1) $(0,1,1)_{12}$	AR (1) φ_1 MA (1) θ_1 SMA (1) Θ_1	0.8050 0.2278 -0.9999	22.500 (<0.01) 3.985 (<0.01) -18.32 (<0.01)
3	SARIMA (1,0,0) $(0,1,1)_{12}$	AR (1) φ_1 SMA (1) Θ_1	0.8617 -0.9999	22.500 (<0.01) -19.597 (<0.01)

Note: φ is the estimate of AR model parameter
θ is the estimate of MA model parameter
Φ is the estimate of the seasonal AR model parameter
Θ is the estimate of the seasonal MA model parameter

fluctuate around a mean of zero, have uniform variance, and are not correlated (**Figure 5**).

Model Evaluation and Forecasting

The selected best model SARIMA (1,0,1) $(0,1,1)_{12}$ indicate that the monthly closing water level of Angat Dam denoted as Z_t is not only reliant on its preceding months' data Z_{t-1}, but also to its preceding shocks a_{t-1} and a_{t-12}. The estimated parameters of SARIMA (1,0,1) $(0,1,1)_{12}$ from the model development set are 0.8050 for AR (1), 0.2278 for MA (1), and -0.999 for SMA (1) (**Table 4**). There were consistent values on the estimated coefficients between models with model development and evaluation set. Since the AIC and BIC decreased for the out-sampled model and parameters were still significant, the model is indeed consistent.

Table 3. Computed p-value for diagnostic checking of residuals and measure of fit of candidate SARIMA models (significance level sets as 5%).

Candidate Models (SARIMA)	Analysis of Residuals				AIC	BIC
	Mean Equal to Zero (t-test)	Constant Variance (ARCH LM Stat)	Normal Distribution (Jaqrue-Bera Stat)	Independence (Q-Stat Box Test)		
1	0.9218	<0.01	<0.01	<0.01	2350.58	2362.24
2	0.8091	0.0664	<0.01	0.8816	2211.76	2227.30
3	0.7938	0.0631	<0.01	<0.01	2224.94	2236.60

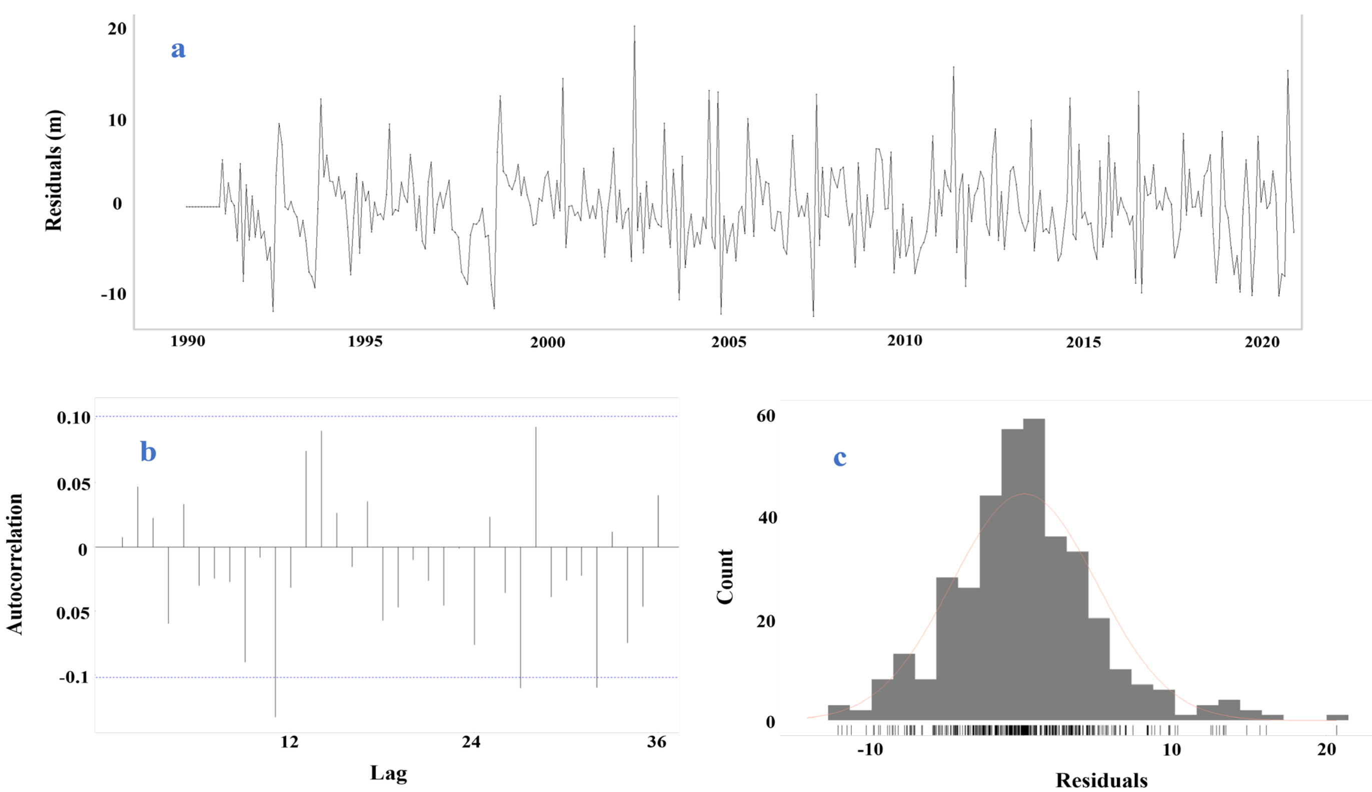

Figure 5. Residual's diagnosis of SARIMA (1,0,1) $(0,1,1)_{12}$ (a) times series plot of residual (b) correlogram (c) histogram plus estimated density.

The time series and scatter plot of the actual versus the fitted water level of Angat Dam were generated with the model SARIMA (1,0,1) $(0,1,1)_{12}$ (**Figure 6**). The fitted values were satisfactory based on the computed RMSE of 4.79 m, MAE of 3.50 m, and NSE of 0.872. The result of MAPE indicated that, on the average, the forecast water levels of SARIMA (0,1,0) $(2,1,0)_{12}$ are off by around 1.8%.

The 12-month lead forecast (January to December 2021) showed 80 and 95% confidence intervals of SARIMA (0,1,0) $(2,1,0)_{12}$ (**Figure 7**). By the end of 2021, the model forecasted an Angat Dam water level of 210.10 m which is higher than the recorded level of 202.80 m. It is observable that as the forecast go further from the last actual data used in the model (December 2020) the uncertainty or the range between the upper and lower limits of confidence intervals increases. To support the validity of SARIMA (0,1,0) $(2,1,0)_{12}$ through time, simulations using additional new actual monthly values of water level on a rolling basis were also evaluated (**Figure 8**). The upper right image shows that with the addition of January 2021 data in the model development, the forecast closing water level for February 2021 (red line) was observed to be closer to the actual value (gray line) compared to the 12-month led forecasts with December 2020 as the last data (blue line) (**Figure 8**). This is consistent with the results on the PACF correlogram that shows the dependency of the current water level with the previous two preceding months (**Figure 5**).

Tabios (*2008*) suggests the need for dynamic and anticipatory reservoir operating strategy in themanagement of Angat Dam with the application of forecasting in actual and real-time reservoir operations.

Table 4. Comparison of parameters estimate of the obtained best SARIMA Model in model development and model evaluation set.

Parameter		Model Development Set (1990-2020)	Model Evaluation Set (1990-2017)
AR (1) φ_1	Estimated Coefficient	0.8050	0.8267
	Significant Error	0.0358	0.0356
	p-value	<0.01	<0.01
MA (1) θ_1	Estimated Coefficient	0.2278	0.1770
	Significant Error	0.0572	0.0595
	p-value	<0.01	<0.01
SMA (1) Θ_1	Estimated Coefficient	-0.999	-0.999
	Significant Error	0.0546	0.0511
	p-value	<0.01	<0.01
AIC		2211.8	1979.4
BIC		2227.3	1994.5
R2		0.93	0.93
RMSE (m)		4.79	4.67
MAE (m)		3.45	3.38
MAPE (%)		1.80	1.73
NSE		0.87	0.88

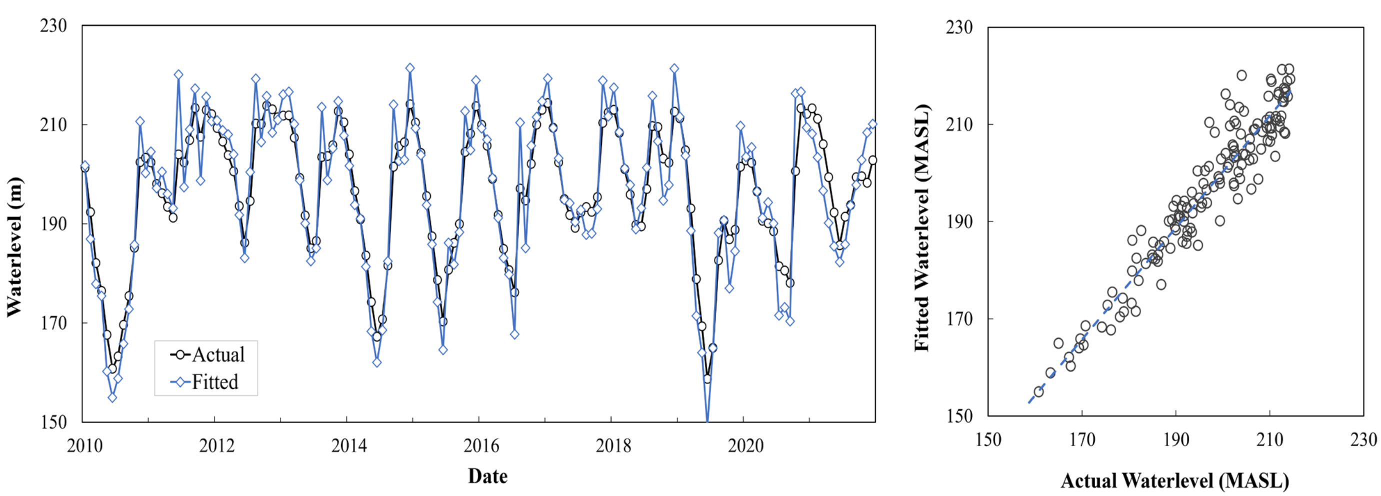

Figure 6. Actual vs fitted Angat Dam monthly closing water level generated from SARIMA (0,1,0) $(2,1,0)_{12}$.

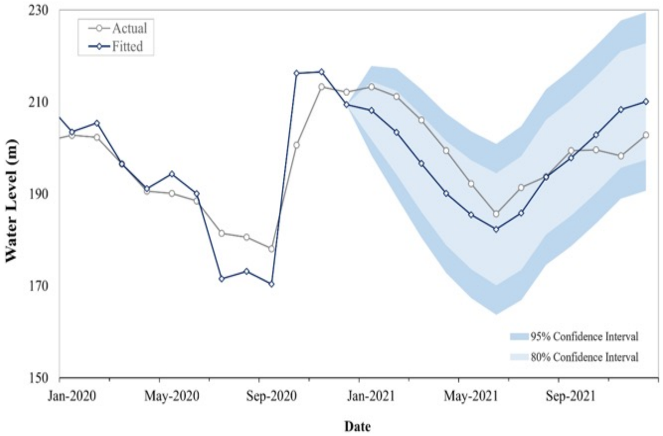

Figure 7. Actual and forecasted Angat Dam monthly closing water level (in meters) from January to December 2021 using SARIMA (1,0,1)(0,1,1)$_{12}$ with in-sampling datasets.

The developed SARIMA model in this study could be a supplement tool for short-term forecasting of Angat Dam water level without looking for the time series of other variables. Modeling of dam water level was a challenge because it should factor in both the watershed's hydro-meteorological response and the reservoir's management and operation.

CONCLUSIONS AND RECOMMENDATIONS

The current reservoir operations procedures in Angat Dam are governed by the rule curve of dam water level. This parameter has been used as indicator variable or the basis for crafting the short-term management of Angat Dam including the water allocation for irrigation and domestic use. Forecasting of this parameter is valuable

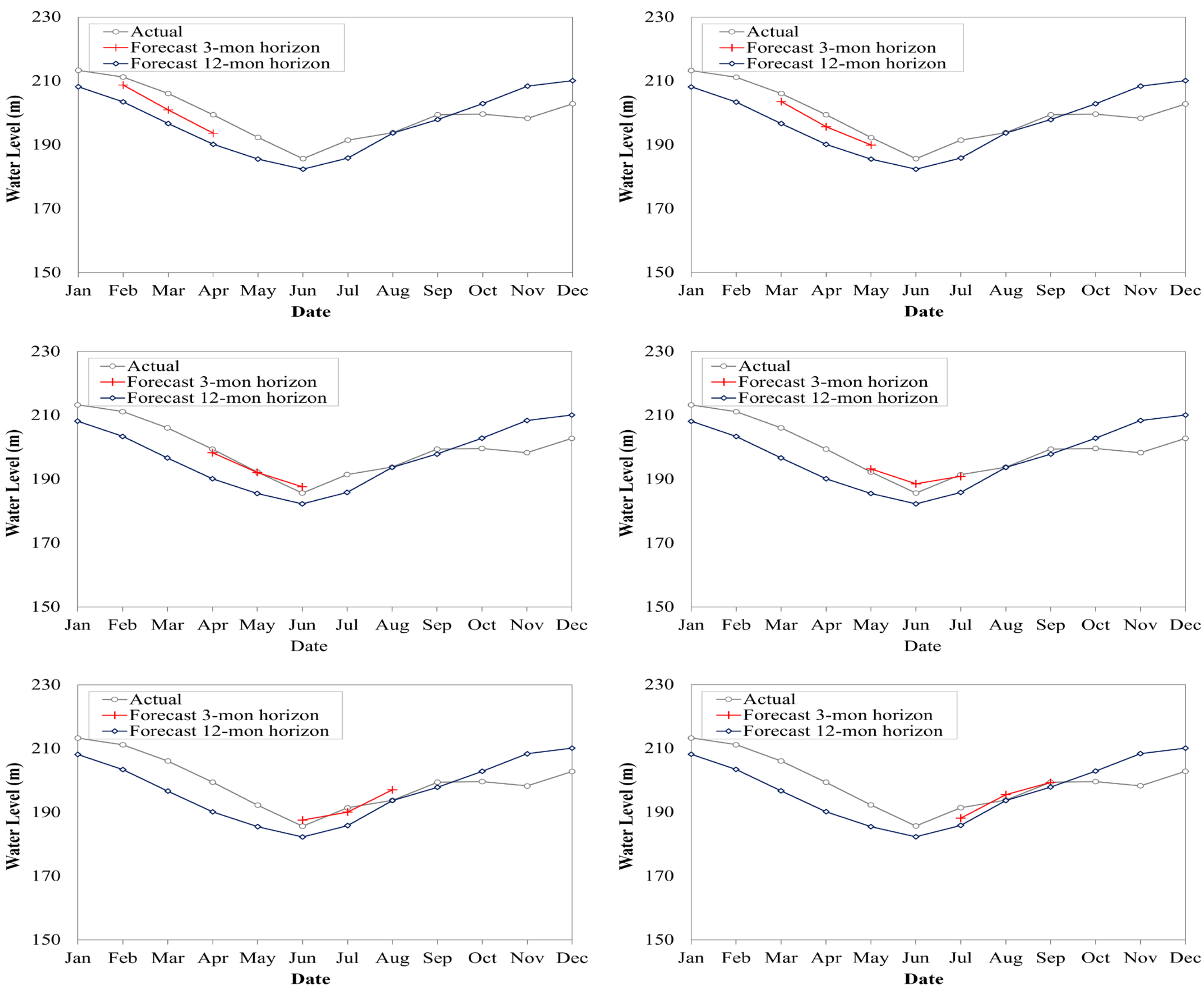

Figure 8. Actual and forecasted Angat Dam monthly closing water level (in meters) from February to July 2021 using SARIMA (1,0,1) (0,1,1)$_{12}$ using the datasets from model development set (blue line) and with additional new actual values (red line). Blue line has 12-month forecasts horizon while the red line has 3-month forecasts horizon.

because it could give decision-makers horizon for planning and executing operations to minimize potential risks and optimize solutions. In this study, time-series analysis was executed to understand the past behavioral pattern and provide short-term forecast of Angat Dam water level. Series decomposition revealed the absence of over-all trend component but presence of seasonality in the dataset. The correlogram shows an almost perfect partial correlation between a certain month's closing water level with that of the preceding two months' closing water level. The best identified model SARIMA $(1,0,1)\ (0,1,1)_{12}$ offers a satisfactory and adequate short-term forecast of the monthly closing water level of Angat Dam with RMSE of 4.78 m, MAE of 3.45 m, NSE of 0.87 and MAPE of 1.8%. This study also demonstrated the adequacy of the model for dynamic forecasting based on real-time updating of monthly data on a rolling basis.

The developed SARIMA model in this study could be improved by implementing SARIMAX which support other important exogenous variable such as rainfall, dam inflow, and demands. Other computational intelligent techniques self-exciting threshold autoregressive (SETAR), multivariate adaptive regression splines (MARS), and random forests (RF) models can be explored in future studies for model comparison and improvement.

REFERENCES

Abudu, S., Cui, C.L., King, J.P. and Abudukadeer, K. 2010. "Comparison of performance of statistical models in forecasting monthly streamflow of Kizil River, China". *Water Science and Engineering* 3(3): 269–281.

Adhikary, S.K. and Gupta, A. Das 2012. "A Stochastic Modelling Technique for Predicting Groundwater Table Fluctuations with Time Series Analysis". *International Journal of Applied Science and Engineering Research* 1(2): 238–249.

Adnan, R.M., Liang, Z., Heddam, S., Zounemat-Kermani, M., Kisi, O. and Li, B. 2020. "Least square support vector machine and multivariate adaptive regression splines for streamflow prediction in mountainous basin using hydro-meteorological data as inputs". *Journal of Hydrology* 586124371.

Box, G. and Jenkins, G. 1976. Time Series Analysis: Forecasting and Control. San Francisco: Holden-Day.

Chang, X., Gao, M., Wang, Y. and Hou, X. 2012. "Seasonal autoregressive integrated moving average model for precipitation time series". *Journal of Mathematics and Statistics* 8(4): 500–505.

Dickey, D.A. and Fuller, W.A. 1979. "Distribution of the Estimators for Autoregressive Time Series With a Unit Root". *Journal of the American Statistical Association* 74(366): 427.

DOE [Department of Energy]. 2023. "List of Existing Power Plants as of August 30, 2023".

DOST-PAGASA [Department of Science and Technology - Philippine Atmospheric Geophysical and Astronomical Services Administration]. 2019. "El Niño Advisory No. 6".

Engle, R.F. 1982. "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation". *Econometrica* 50(4): 987–1008.

Fathian, F., Modarres, R. and Dehghan, Z. 2016. "Urmia Lake water-level change detection and modeling". *Modeling Earth Systems and Environment* 2(4): 1–16.

Gharde, K. 2016. "Developed Seasonal ARIMA Model to Forecast Streamflow for Savitri Basin in Konkan Region of Maharshtra on Daily Basis Developed Seasonal ARIMA Model to Forecast Streamflow for Savitri Basin in Konkan Region of Maharshtra on Daily Basis". *Journal of the Indian Society of Coastal Agricultural Research* 34(1): 110–119.

Hyndman, R., Athanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L., Kuroptev, K., O'Hara-Wild, M., Petropoulos, F., Razbash, S., Wang, E. and Yasmeen, F. 2022. "forecast: Forecasting functions for time series and linear models. R package version 8.18".

Hyndman, R.J. and Athanasopoulos, G. 2013. Forecasting: Principles and Practice. University of Western Australia.

Ibañez, S.C., Dajac, C.V.G., Liponhay, M.P., Legara, E.F.T., Esteban, J.M.H. and Monterola, C.P. 2022. "Forecasting reservoir water levels using deep neural networks: A case study of angat dam in the philippines". *Water* (Switzerland) 14(34): 1–21.

Jaranilla-Sanchez, P.A., Wang, L. and Koike, T. 2011. "Modeling the hydrologic responses of the Pampanga River basin, Philippines: A quantitative approach for identifying droughts". *Water Resources Research* 47(3): 1–21.

Jarque, C.M. 1980. "Efficient test for normality, homoscedasticity and serial independence of residuals". *Economic Letters* 6(3): 225–259.

Jung, G.A. 1978. "On a measure of lack of fit in time series models". *Biometrika* 65(2): 293–303.

Kendall, M.G. 1955. "Rank Correlation Methods". *Charles Griffin & Co.* 9(1): 68–68.

Kokilavani, S., Pangayarselvi, R., Ramanathan, S.P. and Dheebakaran, G. 2020. "SARIMA Modelling and Forecasting of Monthly Rainfall Patterns for Coimbatore, Tamil Nadu , India". *Current Journal of Applied Science and Technology* 39(8): 69–76.

Kwiatkowski, D. and Phillips, P.C.B. 1992. "Testing the null hypothesis of stationarity against the alternative of a unit root How sure are we that economic time series have a unit root ?". *Journal of Econometrics* 54(1–3): 159–178.

Laforga, B. 2019. "Metro Manila most congested developing Asian city - ADB". 26 September.

Machiwal, D. and Jha, M.K. 2006. "Time series analysis of hydrologic data for water resources planning and management: a review". *Journal of Hydrology and Hydromechanics* 54(3): 237–257.

Mann, H.B. 1945. "Non-Parametric Test Against Trend". *Econometrica* 13(3): 245–259.

Metropolitan Waterworks and Sewerage System [MWSS] 2012. "Proposed rehabilitation, operation, and maintenance of MWSS-owned auxiliary turbines AN4 7AN5 at the Angat hydro-electric power plant through Public-Private Partnership".

Moeeni, H., Bonakdari, H. and Ebtehaj, I. 2017. "Monthly reservoir inflow forecasting using a new hybrid SARIMA genetic programming approach". *Journal of Earth System Science* 126(2): 1–18.

Mulumpwa, M.C., Wilson, J., Mathews, L. 2018. "Modelling and forecasting Lake Malawi water level fluctuations using stochastic models". *African Journal of Rural Development* 3(3): 831–841.

National Water Resources Board [NWRB] 2009. "Approval of the New Angat Reservoir Operation Rules, Resolution No. 003-1209". 10 December.

Phillips, P.C.B. and Perron, P. 1988. "Testing for a unit root in time series regression". *Biometrika* 75(2): 335–346.

Rola, A.C. and Elazegui, D.D. 2008. "Role of Institution in Managing Agriculture-Related Climate Risks: Angat Reservoir Case Study, Bulacan, Philippines". *Journal of Environmental Science and Management* 11(1): 26–39.

Sabillo, K. 2019. "Explainer: Why is there a water shortage in Metro Manila?". 12 March.

Tabios, G.Q. and De Leon, T.Z. 2020. "Assessing the Philippine irrigation development program". *PIDS Policy Notes* 2020–02.

Tabios, G.Q.I. 2008. "Angat Reservoir monthly operations using an optimization-simulation model with seasonal autoregressive model to forecast inflows". *Philippine Eng* 29(1): 1–22.

Tadesse, K.B. and Dinka, M.O. 2017. "Application of SARIMA model to forecasting monthly flows in Waterval River, South Africa". *Journal of Water and Land Development* 35(1): 229–236.

Tansengco-Schapero, S., Frauendorfer, R., Klaveren, P. Van, Tan, N. and Bolt, R. 2013. Philippines: Water Supply and Sanitation Sector Assessment, Strategy, and Road Map. Mandaluyong City

Tarakanov, D.A., Elizaryev, A.N., Nyrytdinov, A.A., Elizareva, E.N., Khasanov, I.A., Mikhailov, S.A. and Nutfullina, E.I. 2022. "Ensuring the safety of geotechnical objects based on forecasting the parameters of the water regime of rivers using SARIMA models". IOP Conference Series: *Earth and Environmental Science* 1076(1):

Tejada, A.T., Sanchez, P.A.J., Faderogao, F.J.F., Gigantone, C.B. and Luyun, R.A. 2023. "Spatiotemporal Analysis of Extreme Rainfall and Meteorological Drought Events over the Angat Watershed, Philippines". *Atmosphere* 14(12): 1790.

Torio, P.C., Harris, L.M. and Angeles, L.C. 2019. "The rural–urban equity nexus of Metro Manila's water system". *Water International* 44(2): 115–128.

Trapletti, A. and Hornik, K. 2022. "tseries: Time Series Analysis and Computational Finance. R package version 0.10-52.".

UNESCO - WWAP [United Nations Educational Scientific and Cultural Organization - World Water Assessment Programme] 2021. "The United Nations World Water Development Report 2021:Facts and figures. Valuing Water [SC-2021/WS/3].". United Nations

Valipour, M. 2015. "Long-term runoff study using SARIMA and ARIMA models in the United States". *Meteorological Applications* 22(3): 592–598.

Wang, S., Feng, J. and Liu, G. 2013. "Application of seasonal time series model in the precipitation forecast". *Mathematical and Computer Modelling* 58(3–4): 677–683.

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