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Enhancing Water Level Forecasting Performance in High-Variability Basins through Data Restructuring: A Case Study of the Yom River Basin, Thailand

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Abstract. The Yom river basin in one of the 22 main river basins of Thailand. This experiences perennial floods and droughts that heavily impact the agricultural sector. In order to reduce the impact, water management, including water level estimation. A considerable task of management is the quantitative forecasting of water levels. This study proposes appropriate forecasting models for time series of daily water level data from four water level measurement stations. The study period is from 2007 to 2022 on September. The efficiency of this forecasting model was determined from comparisons to three approaches, centered moving average model (CMA), additive decomposition model (DEC), Holt's Winter additive model (WIN). Results indicated that: The forecasts of two years gave similar forecast patterns to the previously observed values. Mainly, (decomposition) was more accurate than the other approaches for all stations. The RMSEs of upstream was slightly greater than the downstream RMSEs for three approaches.

1. Introduction

Forecasting the water level in high fluctuation basins is of paramount importance for effective water resource management and disaster mitigation. These basins are characterized by rapidly changing water levels due to various factors, such as heavy rainfall or sudden inflows from upstream sources. Accurate and timely water level predictions are vital for preventing floods, managing water supply, and ensuring the safety of both urban and rural communities residing in proximity to these basins. In recent years, advancements in data collection, computational capabilities, and predictive modeling techniques have opened new avenues for improving water level forecasting accuracy. This research endeavors to harness these opportunities by developing innovative forecasting methodologies tailored to the unique challenges posed by high fluctuation

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basins. This study aims to address several key objectives. Firstly, it seeks to enhance our understanding of the complex hydrological processes that govern water level fluctuations in these basins. Secondly, it aims to develop robust predictive models that can accommodate the rapid and often nonlinear changes in water levels. Additionally, the research will explore the integration of real-time data, including weather forecasts, river flow measurements, and historical water level data, into the forecasting process. By achieving these objectives, this research endeavors to contribute significantly to the field of hydrology and advance our ability to forecast water levels in high fluctuation basins. Ultimately, the outcomes of this study have the potential to inform decision-makers, emergency responders, and water resource managers, enabling more proactive and effective responses to mitigate the impact of extreme water level events in vulnerable regions. The Yom river basin in one of the 22 main river basins of Thailand ([1], [2]). Located in Northern Thailand. The Yom river basin is important because of the variety of tropical wet and dry, climates that occur throughout the yaer ([3], [4]). The Office of the National Water Resources reported in 2021 that Yom river basin received average annual precipitation of about 1,264.80 mm. The average annual runoff 3,688 million mm^3, that average annual runoff 3,247 million mm^3 in wet season and 441 million mm^3 in dry season. The water resources development project had 22 projects, with a total storage capacity of 160.84 million mm^3, the gain an advantage of area 146.2112 km^2. The amount of water demand is 4,135.67 million m^3, consisting of agriculture, consumption resistance, industry volume of 4,035.45, 81.48, and 18.74 million m^3, respectively. The floods-prone area of 14,664.84 km^2, consisting of low risk 6,905.76 km^2, moderate risk 5,37 3.12 km^2, and high risk 2,385.96 km^2. The droughts-prone area of 23,452.15 km^2, consisting of low risk 14,571.78 km^2, moderate risk 8,492.80 km^2, and high risk 387.58 km^2. The area is suitable for developing irrigation area of 4,578.1472 km^2 and agriculture area of 2,415.2576 km^2 [1]. There are several factors that affect the streamflow of a river, the streamflow of a river is the integration of climatic factors and the precipitation. Changes in streamflow may be caused by climate change and human activities disturbance. These lead to complication of hydrological modeling ([5], [6], [7], [8]). The water level fluctuations have been increasingly serious due to extreme events and abnormal climate [9].

Nualtong et al., are study proposes hybridized forecasting models between three approaches. Firstly, a stochastic approach, the seasonal autoregressive integrated moving average or SARIMA model; secondly, a machine learning approach, the artificial neural network or ANN model; finally, a hybridized approach, seasonal autoregressive integrated moving average and artificial neural network or SARIMANN model for average monthly water level (AMWL) time series of Yom river basin, the wet season is from May to October and the dry season is from November to April. Results indicated that: The three models reveal the similarity of RMSE and MAPE for both four water level measurement stations for wet and dry seasons. The SARIMA model is the best approach for Y.31 station, Y.20 station, Y.37 station, while the best approach for Y.1C station is the SARIMANN model for wet season. Both the SARIMA model and the SARIMANN model are better than the ANN model in the wet season by RMSE for all stations. Although the downstream is affected by many disturbances, it is still more accurate than the upstream. This is the visible evidence to indicate that the stochastic based models, SARIMA model and SARIMANN model proposed in this study are appropriate for the high fluctuation series. Furthermore, the dry season forecasting is more accurate than the wet season [3]. Nualtong et al., are study proposes appropriate forecasting models for time series of the AMWL of the Yom river basin in Northern Thailand. The approach modified the Box-Jenkins method into a seasonal regression time series model, is called the Dynamic Seasonal Regression (DSR) model, which has been developed from previous works ([10], [11], [12]). The efficiency of this forecasting model was determined from comparisons to three different approaches, ANN model, SARIMA model, and SARIMANN model. The study period was over thirteen hydrological years from April 2007 to March 2020. The DSR model, which was obtained by combining multiple linear regression (MLR) and the autoregressive integrated moving average (ARIMA) model of the random error from MLR. The DSR model was more efficient than ANN model, SARIMA model, and SARIMANN model. The MAPE of upstream was lower than the downstream in both seasons for all methods. The RMSE of upstream was higher than the RMSE downstream in the wet season for all methods, moreover, the RMSE of upstream was lower than the downstream in the dry season for all methods except the ANN method [4]. Okost M. et al., are proposed to the water level in the river as a time series, with the Holt-Winters method. The forecasting model, allows to perform a 7-day forecast of the water level in the Temernik River. The forecasting model under consideration, is quite effective, the correlation ratio of the compared data was 0.97 [13].

This study proposes appropriate forecasting models for time series of daily water level of the Yom river basin. The study period was over sixteen years, from 2007 to 2022 on September. The thirty-time series (day: $1, 2, \ldots, 30$) at each station, the sixteen index (year: $2007, 2008, \ldots, 2022$) at each time series, a total of four water level measurement stations. The efficiency of this forecasting model was determined from comparisons to three different approaches. Firstly, centered moving average model (CMA); secondly, additive decomposition model (DEC); and finally, state space model (WIN). The forecasting performance is the mean absolute percentage error (MAPE), the mean absolute deviation (MAD), the mean squared error (MSE), and the minimum values of root mean squared error (RMSE).

2. Materials and Methods

2.1. **Study Region and Dataset.** The Office of the National Water Resources reported in 2021 that Yom river basin has area of 23,995.556 km^2, consisted 19 major sub-river basins and covers administratively 11 provinces, as shown in Figure 1. The geography of Yom river basin, At slope 300 – 600 m(MSL). The length of the Yom river is approximately 793 km [1]. The Yom river basin between the latitude 14° 50′ N to 18 ° 25′ N and the longitude 99 ° 16′ E to 100 ° 40′ E [4].

The daily water level data in m (MSL) were selected from four water level measurement stations were selected over the length of the main Yom river: Ban Thung Nong [Y.31] station, Ban Huai

Sak [Y.20] station, Ban Nam Khong [Y.1C] station, and Ban Wang Chin [Y.37] station, as shown in Figure 1. The study period in September was over sixteen years, from 2007 to 2022. This is during the wet season and there is the highest amount of water level. Data were collected from the Upper Northern Region Irrigation Hydrology Center, Royal Irrigation Department [16].

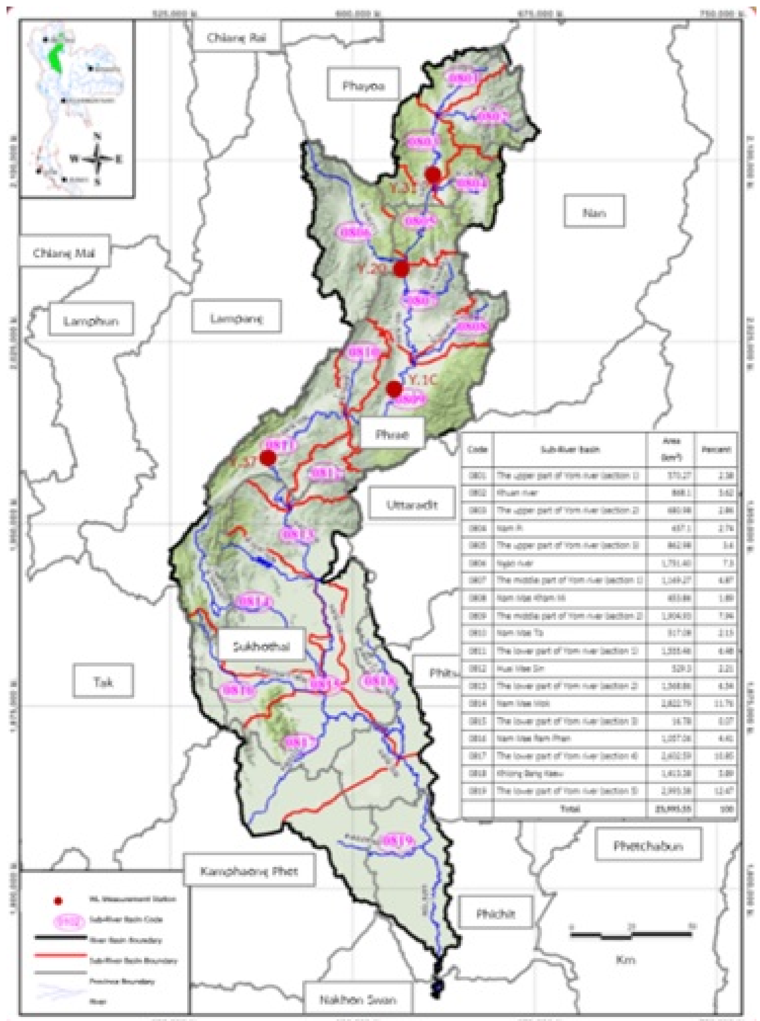

Figure 1. Locations of water level measurement station in Yom river basin.

2.2. **Data Restructuring.** There are 14-years time series of daily water level between September 1st and September 30th, the highest water level period in Yom river basin, Thailand, was collected. It is reasonable for consider this period because there is the highest water level period in this basin, Another reason is avoiding the complicated time series models for predicting the consecutive data points in this period and being comprised year after year. Becaused of these reasons, at each station, we have 30 series of water level to forecast, i.e., series of water level on September 1st from 2007 to 2020, series of water level on September 2nd from 2007 to 2020, . . . , and so on, as shown in Table 1 - 4.

Table 1. 2007-2020 series of water level on the same date from September 1st through September 30th of Y31 station in Yom river basin Thailand.

Year	Series of Sep 1st	Series of Sep 2nd	⋯	Series of Sep 29th	Series of Sep 30th
2007	258.8	258.79	⋯	259.64	259.22
2008	260.41	260.56	⋯	259.46	259.2
2009	259.68	258.95	⋯	258.46	258.39
2010	261.12	260.79	⋯	259.23	259.28
2011	260.33	260.25	⋯	259.78	259.64
2012	259.22	259.3	⋯	260.15	259.7
2013	259.65	259.01	⋯	259.21	258.92
2014	260.88	262.4	⋯	259.25	259.91
2015	258.21	258.75	⋯	258.36	258.3
2016	259.86	259.47	⋯	259.81	259.23
2017	261.34	260.51	⋯	260.16	260.45
2018	259.6	259.53	⋯	259.5	259.59
2019	261.43	260.87	⋯	258.43	258.34
2020	258.37	258.37	⋯	258.39	258.41

Table 2. 2007-2020 series of water level on the same date from September 1st through September 30th of Y20 station in Yom river basin Thailand.

Year	Series of Sep 1st	Series of Sep 2nd	⋯	Series of Sep 29th	Series of Sep 30th
2007	183.6	183.23	⋯	184.57	183.94
2008	184.48	185.37	⋯	183.87	183.73
2009	184.08	184.33	⋯	183.31	182.98
2010	186.14	185.35	⋯	183.66	183.34
2011	184.84	185.04	⋯	185.66	184.8
2012	183.37	183.25	⋯	184.98	184.71
2013	184.31	183.73	⋯	183.97	183.59
2014	186.93	188.47	⋯	183.6	185.01
2015	182.1	182.35	⋯	182.48	182.42
2016	184.33	183.88	⋯	184.01	184.28
2017	185.97	185.25	⋯	184.97	185.74
2018	183.86	183.7	⋯	183.53	183.77
2019	187.42	186.55	⋯	182.66	182.51
2020	182.59	182.51	⋯	182.61	182.51

Table 3. 2007-2020 series of water level on the same date from September 1st through September 30th of Y1C station in Yom river basin Thailand.

Year	Series of Sep 1st	Series of Sep 2nd	⋯	Series of Sep 29th	Series of Sep 30th
2007	145.83	145.28	⋯	146.43	145.83
2008	144.94	146.26	⋯	145.04	145.36
2009	144.9	145.9	⋯	145.62	145.01
2010	149.51	148.39	⋯	145.58	145.35
2011	146.61	147.22	⋯	148.19	147.56
2012	145.79	145.64	⋯	146.84	146.68
2013	148.6	146.8	⋯	146.61	145.79
2014	148.48	149.55	⋯	145.49	145.71
2015	144.33	144.31	⋯	144.54	144.52
2016	146.26	146.06	⋯	145.68	146.48
2017	147.15	147.19	⋯	145.78	147.32
2018	145.46	145.32	⋯	145.05	145.06
2019	150.82	150.63	⋯	144.26	144.29
2020	144.5	144.53	⋯	144.88	144.77

Table 4. 2007-2020 series of water level on the same date from September 1st through September 30th of Y37 station in Yom river basin Thailand.

Year	Series of Sep 1st	Series of Sep 2nd	⋯	Series of Sep 29th	Series of Sep 30th
2007	97.3	96.83	⋯	96.33	97.92
2008	95.83	95.72	⋯	95.45	95.48
2009	96.13	96.77	⋯	97.33	96.53
2010	101.86	100.12	⋯	96.92	96.41
2011	97.54	97.8	⋯	98.36	98.96
2012	97.56	97.32	⋯	97.23	97.17
2013	99.96	99.11	⋯	98.29	97.43
2014	98.21	99	⋯	96.21	95.93
2015	94.53	94.48	⋯	94.87	94.79
2016	97.15	96.94	⋯	96.59	96.42
2017	97.48	97.74	⋯	97.34	97.85
2018	96.46	96.07	⋯	95.57	95.87
2019	100.87	101.85	⋯	94.82	94.79
2020	95.29	95.17	⋯	95.48	95.87

2.3. **Forecasting models.**

2.3.1. *Centered Moving Average Model, CMA.* The centered moving average is used instead of moving average then number of periods is even In statistics, a moving average is a calculation to analyze data points by creating series of averages of different subsets of the full data set. It is also called a moving mean or rolling mean and is a finite impulse response filter. Given a series of numbers and a fixed subset size, the moving average's first element is obtained by taking the average of the initial fixed subset of the number series. The subset is then modified by shifting forward; that is, excluding the first number of the series and including the next value in the subset. A moving average is commonly used with time-series data to smooth out short-term fluctuations and highlight longer-term trends or cycles. The centered moving average, which can be expressed as:

Instead of using a regular moving average when the number of periods is even, the centered moving average is employed. In statistics, a moving average is a method for analyzing data points by calculating a series of averages from various subsets of the entire dataset. It is also known as a moving mean or rolling mean and functions as a finite impulse response filter. When given a series of numbers and a fixed subset size, the initial element of the moving average is computed by averaging the initial fixed subset of numbers in the series. Subsequently, the subset is adjusted by shifting forward, meaning that the first number in the series is excluded, and the next value is included in the subset. Moving averages are frequently used in time-series data analysis to smoothen short-term fluctuations and emphasize longer-term trends or patterns. The centered moving average, expressed as follows:

$$\hat{T}_t = \frac{1}{m}\sum_{j=-k}^{k} y_{t+j}, \tag{2.1}$$

where $m = 2k + 1$. The calculation for the trend-cycle value at time t is determined by taking the average of the time series values over a span of k periods centered around t.

2.3.2. *Additive Decomposition Model, DEC.* When we break down a time series into its constituent parts, we typically merge the trend and cycle elements into a unified trend-cycle component, which is sometimes simply referred to as the trend. Consequently, we conceptualize a time series as consisting of three main components: the trend-cycle component, a seasonal component, and a remainder component which encompasses any other variations present in the time series. We applied additive decomposition procedure from [10], firstly, compute the trend-cycle component $\hat{T}_t$ using $2\times m$-MA and m-MA in case of even and odd number of m respectively. Secondly, calculate the detrended series by subtracting the original series, y_t by previous trend-cycle component $\hat{T}_t$. Thirdly, calculate the seasonal component for each specific season by computing the average of the detrended values within that season, this gives $\hat{S}_t$. Finally, The remainder component is derived by subtracting the estimated seasonal and trend-cycle components from the data, therefore

$$\hat{R}_t = y_t - \hat{T}_t - \hat{S}_t. \tag{2.2}$$

2.3.3. *Holt-Winters' Additive Model, WIN.* This method is an expansion of Holt's exponential smoothing, designed to account for seasonality. It generates exponentially smoothed estimates for the forecast's level, trend, and seasonal adjustment. Specifically, in the seasonal additive approach, the seasonality factor is added to the trended forecast, giving rise to the Holt-Winters' additive forecast. This approach is most suitable for datasets exhibiting both trend and seasonality, where the seasonal patterns remain relatively consistent over time. It produces a curved forecast that effectively captures the seasonal fluctuations in the data. The Holt-Winters' Additive model from [10] is

$$\hat{y}_{t+h|t} = a_t + hb_t + s_{t+h-m(k+1)} \tag{2.3}$$

the level, trend and seasonal components in 2.3 can be expressed as follows:

$$a_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(a_{t-1} + r_{t-1}) \tag{2.4}$$

$$r_t = \beta(a_t - a_{t-1}) + (1-\beta)r_{t-1} \tag{2.5}$$

$$s_t = \gamma(y_t - \ell_{t-1} - r_{t-1}) + (1-\gamma)s_{t-m}, \tag{2.6}$$

where k is the integer part of $(h-1)/m$.

3. Results

The forecast error of all restructured series with CMA, DEC and WIN methods comparing to ANN method from all stations in Yom river basin represented by root mean squared error values (RMSE) by every single series (dates) in September as shown in Figure 3. Figure 3 - 3 demonstrated the forecasting performance of CMA, DEC and WIN methods comparing to ANN method by station. For Y31 station, CMA, DEC and WIN performed quite better than ANN, especially the CMA and DEC for almost every series of September. Similarly for Y20 station except in 11th - 14th and 25th - 28th of September that ANN performed better and the more lower stream, the worse it gets as illustrated in Y1C and Y37 stations, ANN overcomes CMA, DEC and WIN in the middle and the end of September.

September	Y.31 Station				Y.20 Station				Y.1C Station				Y.37 Station			
	CMA	DEC	WIN	ANN	CMA	DEC	WIN	ANN	CMA	DEC	WIN	ANN	CMA	DEC	WIN	ANN
1	0.9236	0.6265	1.0445	1.6177	1.6507	1.2216	0.9613	1.5114	1.934	2.0702	0.6248	1.6293	1.8058	0.8007	1.2724	1.5814
2	0.5456	0.6662	1.6111	1.6177	0.9463	0.6977	2.0289	1.5114	1.8157	0.8831	1.1793	1.6293	1.7379	1.0887	0.3486	1.5814
3	0.8668	0.8913	0.9745	1.6177	0.8605	0.8801	1.6402	1.5114	1.6307	1.1321	1.2431	1.6293	1.8338	0.9827	0.9012	1.5814
4	1.1369	1.3844	0.9451	1.6177	1.4707	1.425	0.5608	1.5114	1.145	1.055	1.3472	1.6293	1.9846	1.4183	0.7635	1.5814
5	0.9137	1.4087	1.237	1.6177	1.3857	1.4883	0.996	1.5114	1.3607	1.3935	1.0107	1.6293	1.3599	1.1694	1.1127	1.5814
6	0.5466	0.697	1.6504	1.6177	0.9101	1.0532	1.7645	1.5114	1.035	1.1087	1.4797	1.6293	1.2415	0.9831	1.1273	1.5814
7	0.9448	0.7334	2.7428	1.6177	0.6384	0.7313	2.5667	1.5114	0.6812	0.9559	2.2557	1.6293	0.9869	0.8149	1.4104	1.5814
8	0.5982	0.4667	1.8386	1.6177	0.8211	0.7824	2.4087	1.5114	0.8273	0.9871	3.0904	1.6293	0.5459	0.6927	1.9097	1.5814
9	1.3288	1.2003	1.1311	1.6177	0.9913	0.9526	1.5142	1.5114	0.444	0.6428	2.7335	1.6293	1.4951	1.7936	3.9033	1.5814
10	0.814	0.7287	0.7878	1.6177	1.0734	1.2	1.3653	1.5114	0.4809	0.8591	1.8758	1.6293	2.231	2.6106	4.218	1.5814
11	0.8376	0.4957	0.9589	1.6177	1.8572	1.6271	2.4937	1.5114	1.2785	1.5544	2.0835	1.6293	1.9677	2.3579	3.2168	1.5814
12	0.9334	0.3032	0.8462	1.6177	2.0098	1.4506	2.2939	1.5114	2.4897	2.1218	2.935	1.6293	2.7509	2.7405	3.4481	1.5814
13	1.4357	0.8956	1.7338	1.6177	1.8626	1.6363	2.3407	1.5114	2.2477	1.9121	2.4683	1.6293	3.0241	2.78	3.5659	1.5814
14	1.3662	1.3433	2.077	1.6177	2.0193	2.1876	3.2113	1.5114	1.8508	1.5942	2.3075	1.6293	2.4782	2.2741	2.9654	1.5814
15	1.0602	0.9653	1.5006	1.6177	1.5212	1.432	2.2234	1.5114	1.771	1.8576	2.6608	1.6293	2.093	1.6892	2.2378	1.5814
16	1.0301	0.4068	1.0393	1.6177	1.1842	0.7478	1.5774	1.5114	1.0451	0.641	1.7579	1.6293	1.783	1.4655	2.2988	1.5814
17	0.7732	0.3582	1.0228	1.6177	0.9193	0.4105	1.6675	1.5114	0.7324	0.153	1.8392	1.6293	1.1197	0.625	2.6403	1.5814
18	0.848	0.6179	1.1983	1.6177	0.7234	0.5432	1.3815	1.5114	0.599	0.1876	1.4362	1.6293	1.1619	0.6418	2.7571	1.5814
19	1.1306	0.9992	1.4371	1.6177	1.6422	1.7576	1.553	1.5114	0.663	0.9	0.8627	1.6293	0.8393	0.1082	1.9176	1.5814
20	0.8001	0.6206	1.1686	1.6177	1.4672	1.0873	1.2124	1.5114	1.7396	1.6761	1.1868	1.6293	0.6486	0.6875	0.9675	1.5814
21	1.1807	1.1716	1.7499	1.6177	0.5496	0.5099	1.3689	1.5114	1.3706	0.931	0.945	1.6293	1.5911	1.2554	1.2459	1.5814
22	0.5909	0.8302	1.7148	1.6177	0.65	0.7143	1.5879	1.5114	0.7776	0.6537	0.8359	1.6293	1.3217	0.868	1.0142	1.5814
23	1.1034	1.2862	2.2396	1.6177	0.8314	1.1703	2.1829	1.5114	0.4561	0.3925	1.1877	1.6293	0.5808	0.988	1.3196	1.5814
24	1.3956	1.6457	2.5378	1.6177	1.3317	1.7246	2.4432	1.5114	0.9186	1.169	1.8267	1.6293	0.6878	0.9307	0.9084	1.5814
25	1.3963	1.4957	2.3602	1.6177	1.7142	1.6497	2.8513	1.5114	1.292	1.4553	2.1348	1.6293	1.3488	1.6648	1.6431	1.5814
26	1.5743	1.4795	2.2136	1.6177	2.0248	1.9882	2.8578	1.5114	1.7153	1.7125	2.4595	1.6293	1.9476	2.1394	2.2424	1.5814
27	1.3769	1.317	1.9105	1.6177	1.911	1.6941	2.4928	1.5114	1.9508	1.8307	2.4679	1.6293	2.597	2.6835	2.8035	1.5814
28	1.3294	1.6865	1.9492	1.6177	1.6432	1.8683	2.3104	1.5114	1.8316	1.6309	2.1067	1.6293	2.6276	2.2534	2.788	1.5814
29	0.877	0.8815	1.8224	1.6177	1.057	1.2599	2.3237	1.5114	1.6362	1.6936	2.1966	1.6293	2.1918	2.0558	2.5538	1.5814
30	0.4546	0.4962	1.6215	1.6177	0.7728	0.7236	2.5607	1.5114	1.2734	1.1625	2.408	1.6293	1.5728	1.8494	2.2119	1.5814

Figure 2. Forecast error (RMSE) of all methods from all stations in Yom river basin by dates in September.

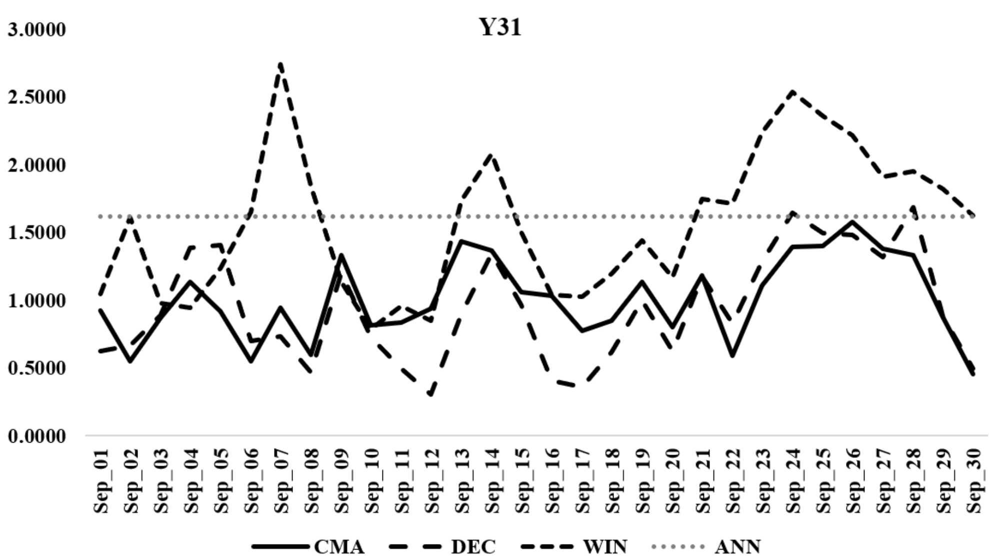

Figure 3. Forecast error (RMSE) of all methods compared with ANN from Y31 stations in Yom river basin by dates in September.

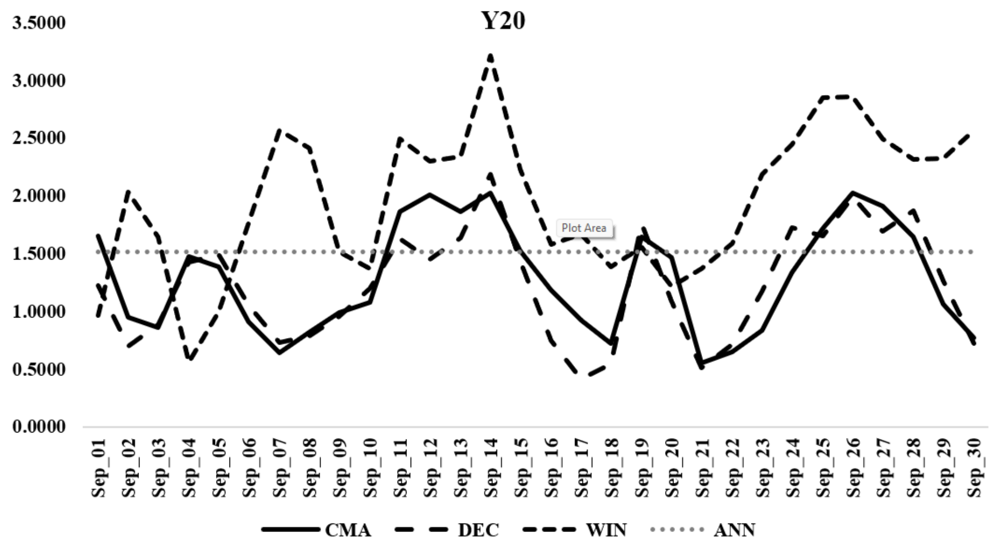

Figure 4. Forecast error (RMSE) of all methods compared with ANN from Y20 stations in Yom river basin by dates in September.

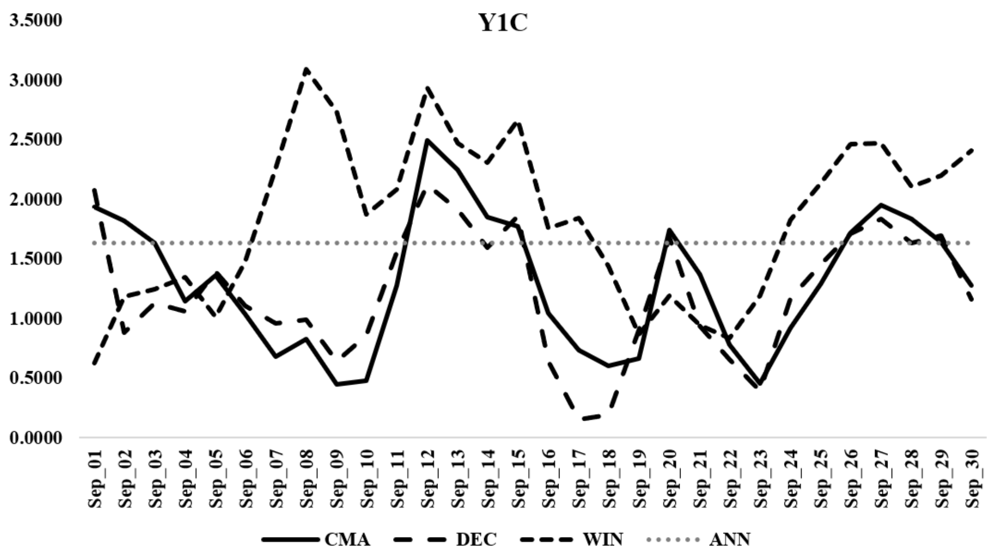

Figure 5. Forecast error (RMSE) of all methods compared with ANN from Y1C stations in Yom river basin by dates in September.

FIGURE 6. Forecast error (RMSE) of all methods compared with ANN from Y37 stations in Yom river basin by dates in September.

4. DISCUSSION AND CONCLUSIONS

All approaches were performed to forecast the daily water level data of four water level measurement stations of the Yom river basin for the months with heavy rainfall on September, the thirty-time series (day: $1, 2, \ldots, 30$) at each station, a total the ninety-time series of four water level measurement stations. The fitting model with fourteen-years (2007 - 2020) of data and forecasting two-years (2021, 2022) at each time series. The forecasts of the three approaches of daily water level data from all four water level measurement stations of two years gave similar forecast patterns to the previously observed values. Mainly, the additive decomposition model (DEC) was more accurate than the other approaches for all stations. The RMSEs of upstream was slightly greater than the downstream RMSEs for three approaches. Furthermore, the accuracy of this forecasting model was determined from comparisons to the artificial neural network (ANN) approaches, forecast the average monthly water level (AMWL) data of all four water level measurement stations for wet seasons (six months: May 2019 – October 2019) of one hydrological year ([4], [5]). The additive decomposition model (DEC) was more accurate than the ANN approaches for Y.31 stations, this the upstream.

In our pursuit of a thorough understanding of water level forecasting, we employed a diverse range of advanced methodologies with great precision. These methods were carefully devised and systematically applied to anticipate the daily water level fluctuations at four strategically situated measurement stations within the Yom river basin. Our primary focus in this forecasting initiative was directed towards the tumultuous months characterized by intense rainfall, with a specific emphasis on the month of September. Throughout this undertaking, we covered the entire month of September comprehensively, meticulously recording and monitoring each day. This meticulous daily monitoring, spanning a period of thirty days, contributed significantly to our in-depth comprehension of the intricate dynamics governing water levels within the basin during this critical timeframe. In total, the dataset we amassed and rigorously analyzed comprised an impressive ninety-time series, resulting from the amalgamation of data originating from these four water level measurement stations. Each of these time series encapsulated a wealth of valuable information, providing valuable insights into the complex interplay of factors influencing water levels within the Yom river basin during the challenging rainy period of September. The painstaking execution of these methodologies, coupled with the wealth of time series data, laid the groundwork for a comprehensive analysis. This analysis is poised to significantly enhance our insights into the hydrological behavior of the Yom river basin under critical weather conditions. Furthermore, this initiative has the potential to guide decision-making processes, enhance flood management strategies, and contribute to the sustainable management of water resources within the region.

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