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The relationship between Atmospheric Variables and Interflow Using the Modified Analog Method over the Storage Dam in Thailand

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Abstract

In this study, we do a simulation of the interflow of storage dams using statistical downscaling by an analog method over the northeast of Thailand. Statistical downscaling is used to define a relationship between atmospheric variables and interflow. Atmospheric variables are predictors such as mean sea level pressure, moisture, geo-potential height and temperature for an interflow simulation. Interflow is used as an observation or a predictand of the reservoir inflow at the stations. The Modified Analog Method is used in interflow simulations for the prediction.The data was acquired from the Water Operation Center from 2000 to 2009 at the four stations and compared with data of the inflow during the month of September 2017. Then, all forecasted data was analyzed and compared at each of the stations to determine the

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correlations between atmospheric variables and interflow for validation. The result showed that the MAM gave the correlation value of one, resulting in a reduced error percentage of 1.53%. The MAM gave the value of 290.71 mcm which was a different value of 309.61 mcm from the observed interflow in the dam.

1 Introduction

Currently, there are 35 dams in Thailand, large and medium in size. These dams were built to block the waterways, used in water retention, flood prevention, and electricity generation. Each dam is classified based on its construction material, such as concrete, rock fill, or earth dam [1]. There are many benefits of dams including retaining water for agriculture and consumption during water shortage, preventing floods during the monsoon season, and generating power. Some dams are also used as tourist attractions and places for recreational activities such as fishing and boating. With its various benefits, the dam is an important water reservoir. Water is essential to the life of all living beings including humans. The population growth rate is likely to increase every day and the earth is experiencing climate changes. Therefore, it is likely that there will be a problem of water shortages in the future. That will increase the severity of the existing drought crisis. Consequently, it is necessary that the water management process be prepared to provide solutions to future issues. In the past, Thailand has encountered multiple crises of drought and severe flooding.

From the report of the Royal Irrigation Department, a summary report of the Smart Water Operations Center [2] analyzed the water situation and the surveillance on July 21, 2019. It was found that the amount of water in the large and medium reservoirs had continuously been decreasing. The actual amount of water that could be used was only 24%, and the amount of water in the dams in Thailand had continuously been decreasing. From the water situation report, the conditions of water in the large and medium-sized reservoirs could be divided into 4 parts as follows:

1). The volume of water in the reservoir was 36,429 million cubic meters, equivalent to 48%. In other words, the usable water volume was 12,280 million cubic meters, representing 24%.

2). The volume of water in the reservoir compared to the year 2018, which was 47,997 million cubic meters, was 63% less than 2018 which was 11,816 million cubic meters.

3). The amount of water flowing into the reservoir was 68.63 million cubic

meters.
4). The amount of drainage water was 126.60 million cubic meters which made the dams able to receive another 39,887 million cubic meters of water. The amount of water in a large reservoir could be categorized as followed:
1. The total amount of water was lower than 30% in 19 places
2. The total amount of water was 31-50% in 10 places.
3. The total amount of water was more than 50% in 6 places.
From the data,we see that the amount of water in the dam is likely to decrease further while the growth rate of the population and the demand for consumption increase.

The problems with water resources can be identified as follows:
1. Problems of having too little water.
2. Problems of having too much water.
3. Problems of waste water and other factors.
As a result, the prediction of the amount of water flowing into the reservoir in advance is quite accurate. It is necessary to accelerate the study of mathematical models to help forecast and to lessen the water management process and large data resources which can help increase the efficiency of water management in reservoirs greatly, especially in the prediction of the amount of water flowing into the reservoir. The mathematical models enable the appropriate support for the amount of water flowing into the reservoir and the ability to keep the downstream water flow at a moderate level which will also reduce the impact on the people living along the downstream riverbanks. To prevent future disasters, such as drought conditions caused by water shortages or flooding caused by the continuous rise in water levels, past and current data must be collected and calculated using a mathematical model to help predict the amount of water entering the reservoir in advance and study the relationship between atmospheric variables and interflow. Using the Modified Analog Method in the northeast of Thailand, atmospheric variables such as mean sea level pressure, moisture, geo-potential height and temperature were predictors for interflow simulation. Interflow was used as an observation or a predictand of the reservoir inflow at the stations. Predictands were predicted local weather variables or precipitation forecasts, inflow forecasting and predictors such as mean temperature, geo-potential height, sea level pressure, humidity and relative humidity [3] by using as choices in downscaling for predictor variables. Downscaling is the process of relocating coarse resolution GCM to fine spatial scale (ground station) data [4]. In creating the GCM model of at least 10-year observed data for the dam in flow forecasts, observed data from 2009 to 2010 available from the observation of

rainfall in the dam flow in the northeast at 4 stations was used. In explaining the basis of the relationship between atmospheric variables and interflow in one of the processes, statistical downscaling techniques were used [5, 6, 7].

In this study, inflow forecasting was based on an analog method for daily interflow in storage dams and the results showed the forecasted inflow into the storage dams. The findings also showed that the forecasted inflow was more accurate in comparison with the observation of interflow in storage dams.

In Section 2, we present an overview of the study area and data used in this research. In Section 3, we introduce the methodology for calculating the Modified Analog Method (MAM) and the performance criteria for forecasted inflow into the storage dams. In Section 4, we present the results of various analyses. Finally, we draw conclusions of the study in Section 5.

2 Data and Domain

In this study, the data examined came from The National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) and The NCEP Climate Forecast System Version 2 (CFSv2) 6-hourly, which were produced by the National Centers for Environmental Prediction (NCEP) Climate Forecast System (CFS).

The initial conditions for comparison of CFSR from the year 2000 to 2009 (Analysis data) were at 0000, 0600, 1200, and 1800 UTC each day and CFSv2 in the year 2017 (Forecast data) was initialized four times per day (0000, 0600, 1200, and 1800 hrs UTC) at the resolution of 0.5×0.5 degrees latitude-longitude. A summary of data sources of atmospheric variables as shown in Table 1 [8, 9, 10, 11, 12].

The datasets of variables were Mean sea level Pressure (MSLP) (hPa), Moisture at 850 hPa height (Q850) (g kg^{-1}), Geo-potential height 850 hPa height (G850) (m) and Temperature at 850 hPa height (T850) (^oC). The data of the actual daily interflow from the year 2000 to 2010 at the Water Operation Center was used to validate against the current year (2017).

In the standard analysis of the actual daily interflow at the storage dams in Thailand, the past interflow data from 2000 to 2009 was recorded with measurement tools such as the rain gauge. Figure 2 shows the daily interflow (mcm/day) during the month of September 2017 at the 4 stations [2].

The study domain only covered the areas of Thailand between latitudes of 4°N to 22°N and longitudes of 95°E to 110°E. The model domain of CFSR

Table 1: A summary of data sources of atmospheric variables.

	Climate Forecast System Reanalysis (CFSR)	**Climate Forecast System (CFSv2)**
Time period	2000 to 2009	2017
Original spatial resolution	$0.25° \times 0.25°$	$0.5° \times 0.5°$
Original time resolution	6 hours	6 hours

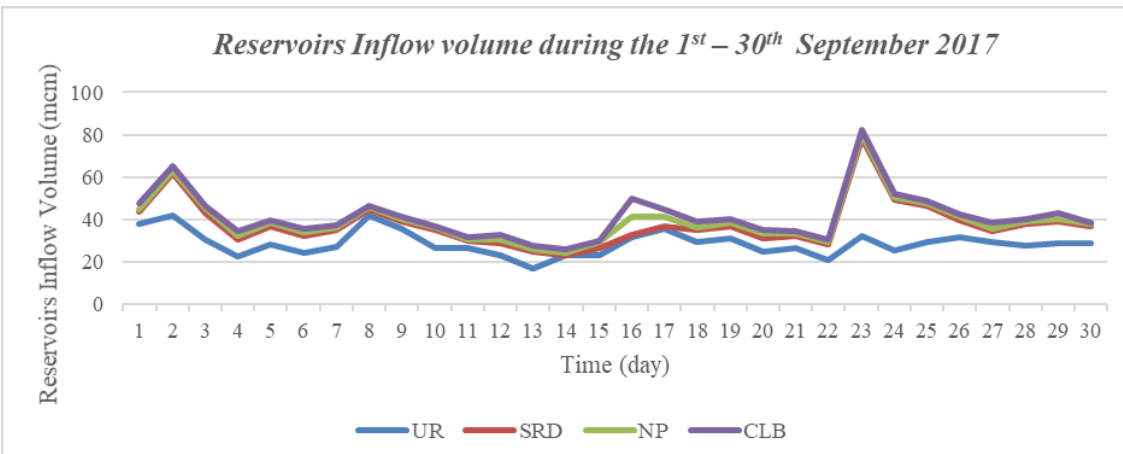

Figure 1: Reservoirs Inflow volume during the month of September 2017 at the 4 stations.

and CFSv2 covered the area between latitudes of 90°S to 90°N and longitudes of 180°W to 180°E. The locations of the storage dams in Thailand for downscaling at the 4 stations (2000-2009) were in one region, the northeast.

The locations of the reservoir information over the northeast of Thailand that had been used in the experiments were shown in Table 2 and Figure 2.

3 Methodology

3.1 Modified Analog Method

The Modified Analog Method (MAM) is a simple statistical downscaling method which is based on the selection of similar atmospheric states. The performance of the MAM depends on the degree of similarity. Wetterhall

Table 2: Reservoir information over the northeast of Thailand.

Stations Name	Stations Location	Catchment capacity (Million Cubic Meter/MCM)			Volume (Million Cubic Meter/MCM)
		maximum	normal	lowest	
Ubolratana dam (UR)	Ubonrat District, Khon Kaen Province	4,640	2,431	581	1,850
Sirindhorm dam (SRD)	Sirinthorn District, Ubon Ratchathani Province	1,966	1,966	831	1,135
Nam Phung Dam (NP)	Kut Bak District, Sakon Nakhon Province	200	165	8	157
Chulabhorn Dam (CLB)	Khon San District, Chaiyaphum Province	181	164	37	127

et al. [13]-[14] described that the basic idea of the Analog Method was to find predictors from the historical record with the same characteristics as predictors at a given target time.

Let $FD(t)$ be predictors from $CFSv2$ in the year 2017 (Forecast data)

$$FD(t) = [FD_1(t), \ldots, FD_L(t)]. \tag{3.1}$$

Let $AD(t)$ be predictors from $CFSR$ in the year 2000 to 2009 (Analysis data).

$$AD(t) = [AD_1(t), \ldots, AD_n(t)]. \tag{3.2}$$

Therefore, Euclidean distance for Analog Method to find analog day was defined as in Equation 3.3.

$$D = \sqrt{\sum_{n=1}^{N} [FD_n(t) - AD_n(t)]^2}. \tag{3.3}$$

The forecast predictor during the month of September 2017 (Forecast data, d) was the predictor from the observations during the month of September from the year 2000 to the year 2009 (Analysis data). N stands for the number of grid points ($n = 1, \ldots, N$). The analog days of the Analog Method for each forecast day were determined from the corresponding days of the analysis data.

3.2 Statistical Analysis

In order to determine the distribution of values among the rainfall forecasts of Predictors (Forecast value) and the Mean Values of OBS (Observed rainfall),

Figure 2: The location map of the study area in Thailand.

statistics such as correlation, error, and bias were calculated in R [15]-[16]. The correlation was based on Pearsons product-moment correlation coefficient following a t distribution with two degrees of freedom.

The root mean square error (RMSE) was calculated as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_0 - P_m)^2}$$

where P_0 and represented the differences between the simulated and observed values, respectively. The percent bias was calculated as follows:

$$Bias = 100 \times \frac{\sum_{i=1}^{n}(P_0 - P_m)}{\sum_{i=1}^{n}(P_0)}$$

The correlation, $RMSE$, and the percent bias measuring the effectiveness were the main basis for answering the research question of whether or not the reanalysis was necessary. This statistical analysis provided a good representation of the accuracy of the models as a whole.

The steps for the simulation of the MAM were shown in Figure 3.2.

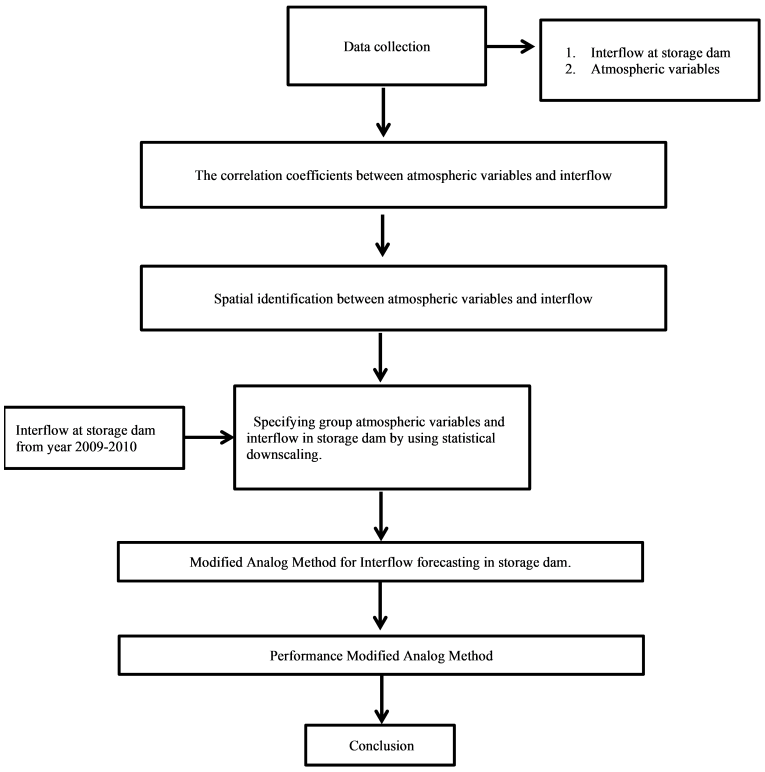

Figure 3: The process of the MAM in this study.

4 Results and Discussion

The modified analog methods of daily simulated interflow from the experiment cases were summarized in Tables 3 - 7.

In this experiment's cases, the monthly simulated interflow was investigated. The simulations of interflow were determined by using the MAM at 0000, 0600, 1200, 1800 UTC with the Water Operation Center at the 4 stations. The predictors for simulated interflow were T850, G850, Q850 and MSLP. The results were compared with simulated interflow and observed (OBS) during September 2017. The monthly results of interflow by the MAM were shown in Tables 3 - 7, respectively.

Tables 3 - 6 and Figures 4 - 8 show the differences between water interflow simulations and observations by the values of simulations of water interflow during the month of September 2017 at each station. The MAM gave the

Table 3: Shows the correlation between interflow simulated and observed from predictors by the MAM at 0000 UTC. to forecast predictors during September 2017 at 4 stations in Thailand.

Station Name	T00	S00	G00	P00	OBS
UR	1485.10	1032.91	867.77	753.67	860.14
SRD	642.94	320.11	555.57	443.95	268.39
NP	42.72	43.21	47.55	39.33	53.45
CLB	40.2515	91.1438	35.0363	38.0833	56.4607
Correlation (r)	0.99	1.00	0.93	0.95	

Table 4: Shows the correlation between water interflow simulated and observed from predictors by the MAM at 0600 UTC. to forecast predictors during September 2017 at 4 stations in Thailand.

Station Name	T06	S06	G06	P06	OBS
UR	1359.19	1091.91	879.30	655.18	860.14
SRD	491.25	346.10	563.38	343.53	268.39
NP	48.78	54.66	45.21	41.49	53.45
CLB	90.2088	72.4672	36.8853	36.3585	56.4607
Correlation (r)	1.00	1.00	0.93	0.97	

Table 5: Shows the correlation between water interflow simulated and observed from predictors by the MAM at 1200 UTC to forecast predictors during the month of September 2017 at 4 stations in Thailand.

Station Name	T12	S12	G12	P12	OBS
UR	679.84	768.44	641.51	611.99	860.14
SRD	396.32	449.42	342.62	426.70	268.39
NP	38.05	55.01	34.29	51.52	53.45
CLB	41.0892	45.0938	47.5075	44.2793	56.4607
Correlation (r)	0.95	0.95	0.97	0.91	

Table 6: Shows the correlation between water interflow simulated and observed from predictors by the MAM at 1800 UTC. to forecast predictors during September 2017 at 4 stations in Thailand.

Station Name	T18	S18	G18	P18	OBS
UR	61994.02	1460.53	858.46	663.17	860.14
SRD	648.75	532.86	640.10	397.82	268.39
NP	64.61	53.02	35.14	45.06	53.45
CLB	79.2519	67.5356	45.2894	59.1856	56.4607
Correlation (r)	1.00	1.00	0.89	0.95	

maximum correlation in every time period (0000, 0600, 1200, and 1800 UTC). As for four variables, the MAM gave the maximum correlation, Therefore, the results in the experiment cases of simulations of water interflow on a downscale monthly show that that the simulations of water interflow were in a good fit for monthly simulations of water interflow.

Table 7: Shows the correlation between simulations of water interflow and observations from predictors by MAM. to forecast predictors during the month of September 2017 at 4 stations of Thailand.

Station Name	T18	S18	G18	P18	OBS
UR	1379.54	1088.45	811.76	671.00	860.14
SRD	544.81	412.12	525.42	403.00	268.39
NP	48.54	51.48	40.55	44.35	53.45
CLB	62.70035	69.0601	41.18	44.476675	56.4607
Correlation (r)	0.99	1.00	0.93	0.95	
sum	508.90	405.28	354.73	290.71	**309.61**
diff	199.29	95.67	45.12	18.90	
MAPE(%)	16.09	7.72	3.64	1.53	

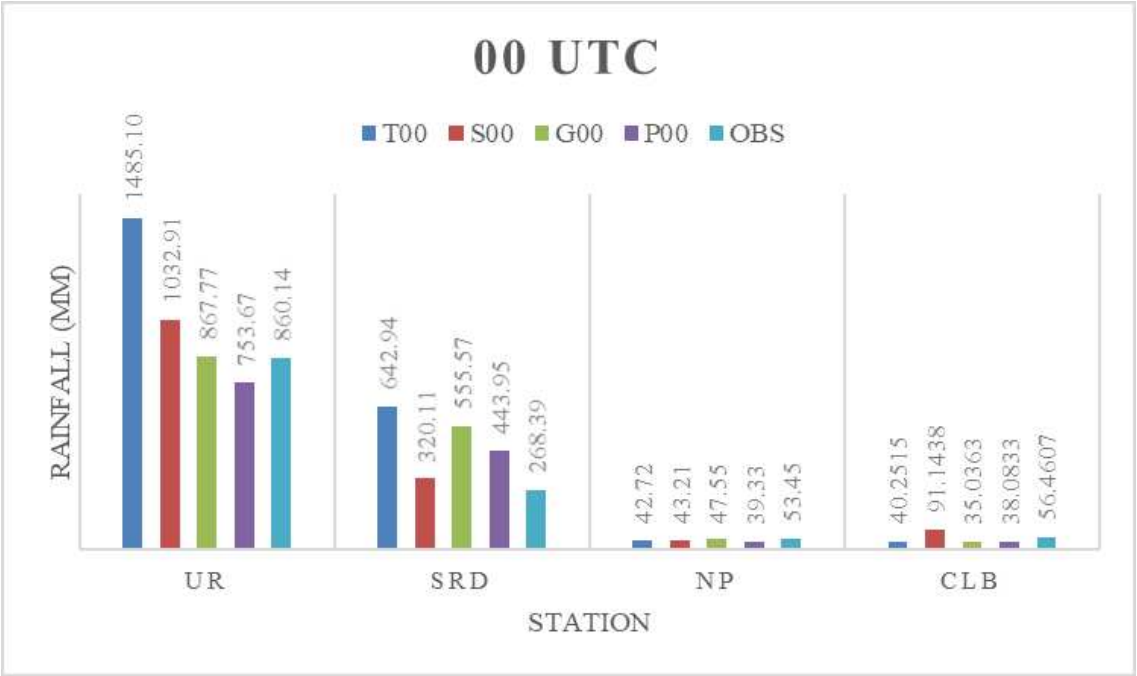

Figure 4: Shows the histogram of the comparison of water interflow simulated and observed at the 4 stations for four predictors, represented in Temperature (T00) and Mean sea level pressure (S00), Geopotential height (G00), Moisture (P00) at 850 hPa of MAM decomposition at the 4 stations.

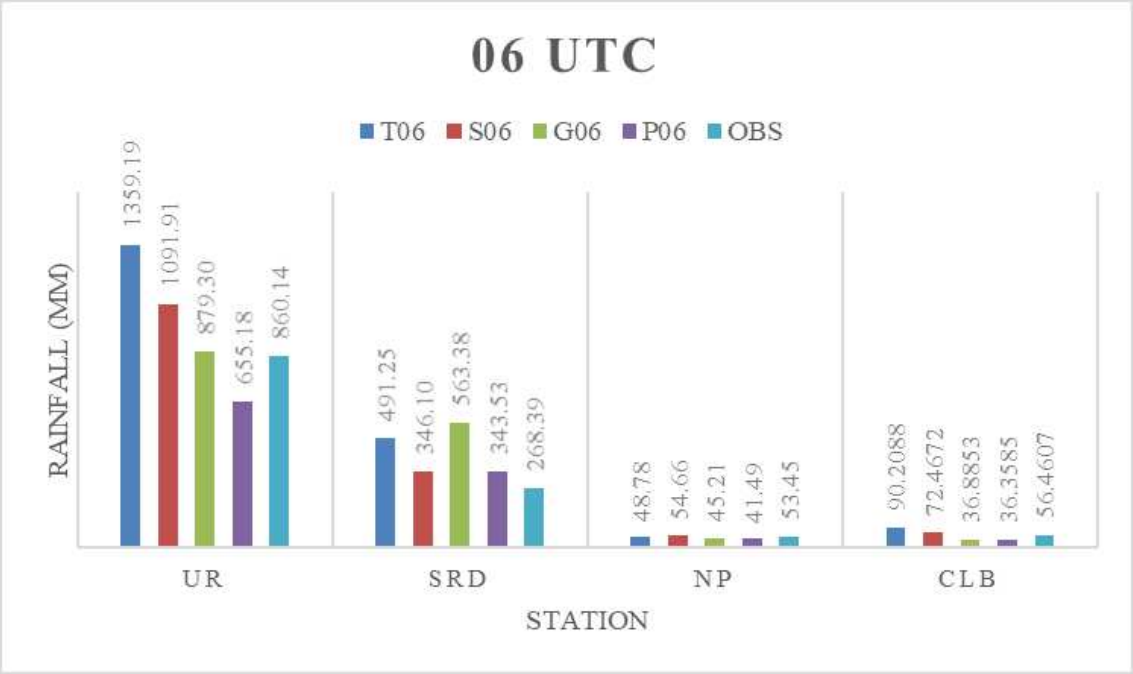

Figure 5: Shows the histogram of the comparison between water interflow simulated and observed at the 4 stations for four predictors, represented in Temperature (T06) and Mean sea level pressure (S06), Geopotential height (G06), Moisture (P06) at 850 hPa of MAM decomposition at the 4 stations.

From Table 7, the simulations of water interflow using the T850 (blue), S850 (red), G850 (green), P850 (purple) and OBS (sky blue) gave 508.90 mcm., 405.28 mcm., 354.73 mcm., 290.71 mcm., 309.61 mcm. respectively. The simulations of water interflow using the MAM with different predictors gave absolute errors of 199.26, 95.67, 45.12, and 18.90 mcm. for T850, S850, G850 and P850 respectively. The results show that the average sum of simulations of water interflow P850 (purple) in September was 290.71 mcm. which was close to the average of the OBS, 309.61 mcm as shown in Figure 4.

Therefore, this results in the minimum error percentage (green) for P850 which was determined as a predictor. The MAM gave the minimum error percentage for the P850 (1.53%) which showed that the value from simulations of water interflow was close to the actual observed value. This was another way showing that the application of statistical downscaling could be used for the simulations of water interflow by using the MAM with the

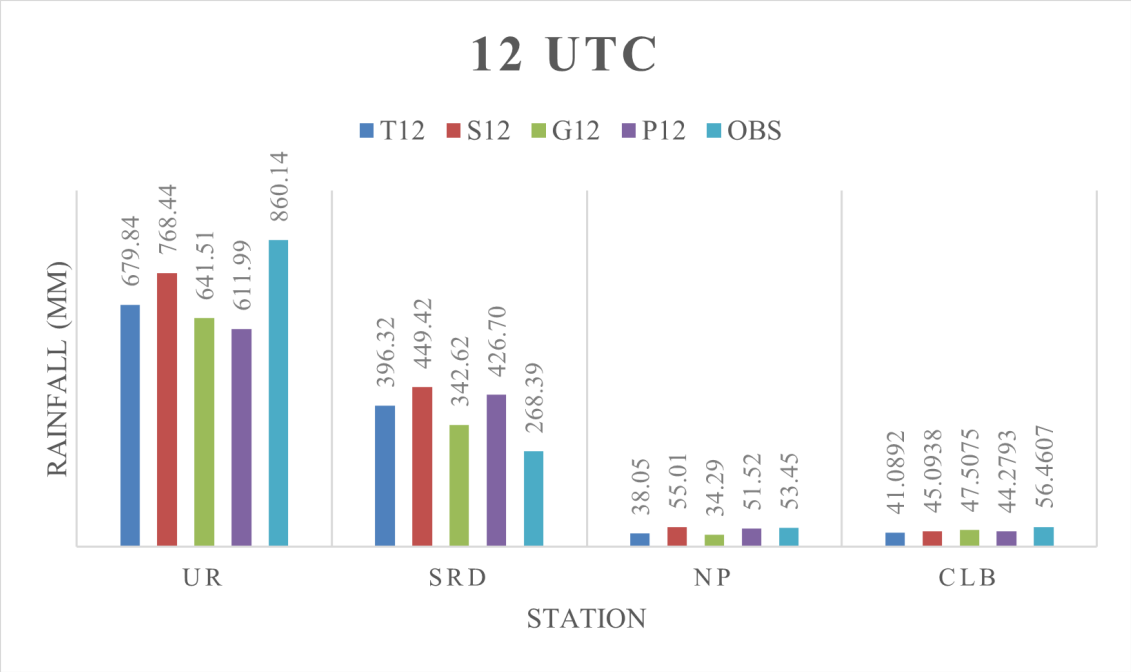

Figure 6: Shows the histogram of the comparison between water interflow simulated and observed at the 4 stations for four predictors, represented in Temperature (T12) and Mean sea level pressure (S12), Geopotential height (G12), Moisture (P12) at 850 hPa of MAM decomposition at the 4 stations.

P850 in Thailand and time (day) during September 2017. Figure 4 shows the scatter plots of observations (horizontal axis) and simulations of water interflow (vertical axis) from all predictors for the MAM.

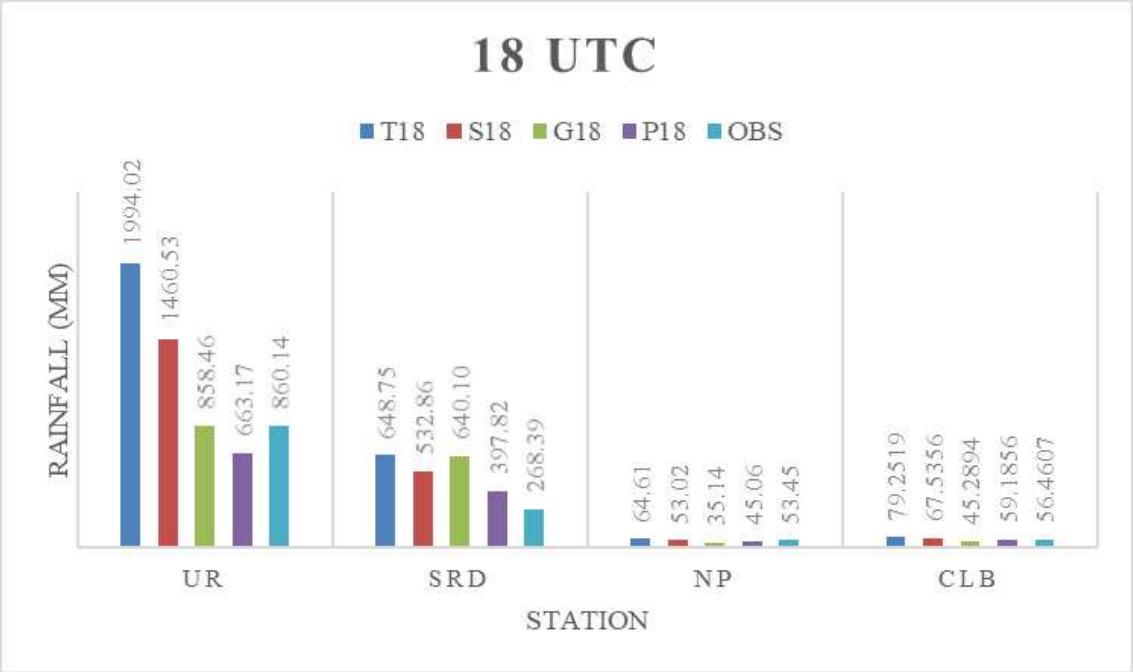

Figure 7: Shows the histogram of the comparison between water interflow simulated and observed at the 4 stations for four predictors, represented in Temperature (T18) and Mean sea level pressure (S18), Geopotential height (G18), Moisture (P00) at 850 hPa of MAM decomposition at the 4 stations.

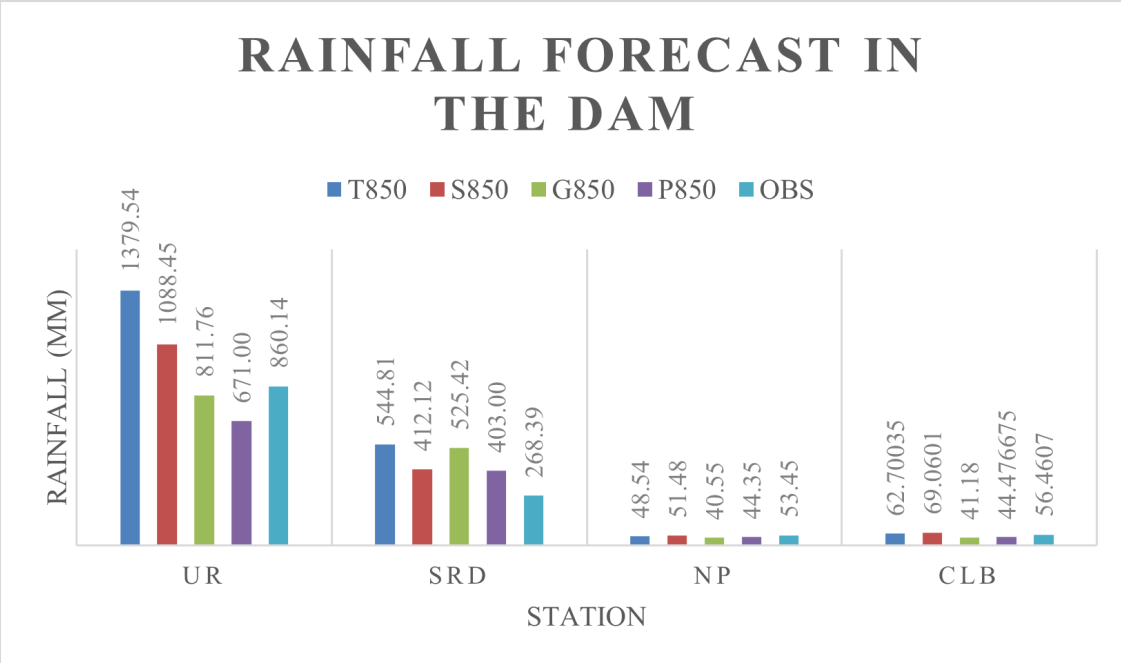

Figure 8: Shows the histogram of the comparison between simulations of water interflow and observations from four predictors, represented in Temperature (T850) and Mean Sea level pressure (S850), Geopotential height (G850), Moisture (P850) at 850 hPa of MAM decomposition at 4 stations.

5 Conclusion

Using MAM, we investigated the simulations of water interflow at 4 stations in the northeast of Thailand. We simulated water interflow using the MAM. The results of the experimental cases of daily downscale simulations of water interflow at 0000, 0006, 1200, and 1800 UTC presented the value of a correlation using four variables as predictors. In each case in this study, we found that simulations of water interflow with MAM showed a minimum error percentage compared to the observed interflow and that the correlation was close to the value of moisture by the MAM with stations giving different values of the rainfall forecast and similar water interflow data to the observation. Therefore, we concluded that MAM was appropriate for water interflow simulations and water interflow was the key factors in water management.

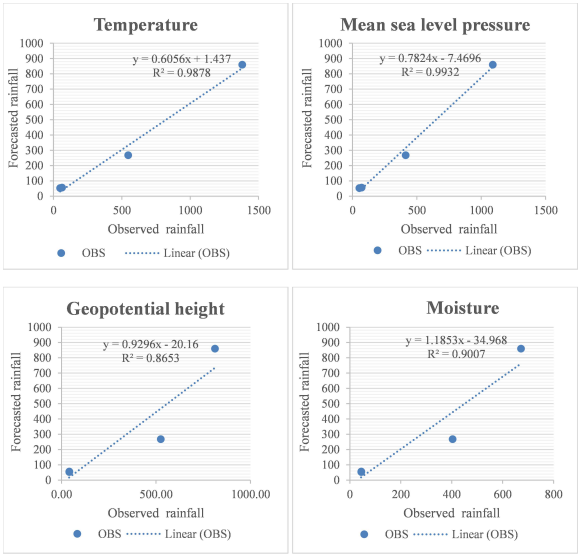

Figure 9: shows the scatter plots of observed (horizontal axis) and simulations of water interflow (vertical axis) from all predictors for the MAM.

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