SEASONAL STREAMFLOW FORECASTS BASED ON PHYSICAL-BASED MODEL FOR CHAO PHRAYA RIVER BASIN IN THAILAND

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***Abstract*— Seasonal forecasts of river flow are crucial for river management in Thailand. The forecasted data can support a water manager to operate the reservoir more effective. The current status of seasonal climate forecast studies shows the evidence that the ability of a forecast will lower during the spring season (February to May), which called spring predictability barrier (SPB). However, there is still no evidence on how much of effect from lower forecast skill during spring in seasonal forecast data to seasonal streamflow forecast. Thus, this study aims to verify the effect of SPB on a streamflow forecast. This study presents the development of a seasonal streamflow forecast dealing with a physical model-based system to produce probabilistic seasonal streamflow forecasts in Chao Phraya river basin. The hydrological model, The H08 model, is forced with the observed meteorological dataset (1981-2004) to verify the model accuracy. The hindcast is simulated using the bias-corrected output of a seasonal rainfall forecast provided by the previous study.The current study, the ability to forecast is compared with observed river discharge and simulated river discharge from the H08 model. Last, we verify the accuracy of seasonal streamflow forecast due to the effect of SPB. Overall, results show that the hindcast simulation in August and November have better agreement with observed river discharge and simulated river discharge than prediction during spring (February to May). The accuracy during the effect of SPB is dramatically dropping when compared to other period. This study recommends that the prediction during spring should be improved in the hydrological model and seasonal climate prediction.**

Keywords—Seasonal Streamflow Forecasts, Spring Predictability Barrier, Seasonal Rainfall Forecasts, Hydrological Model

I. INTRODUCTION

A seasonal predictionis needed for effective water resource management such as flood protection and mitigation. At seasonal predictions scale (up to 6-monthlead-time) are beneficial to water management in terms of timely enough for reservoir operation. Water manager needs to make a decision on reservoir operation especially during the end of the dry season to wet season such as Chao Phraya River Basin (CPRB) that located in Thailand. However, there was an issue on the low accuracy of seasonal prediction for climate variables on spring, which is so-called “spring predictability barrier (SPB)”, is identified critical issue for seasonal prediction in global scale [1].

Recent studies on streamflow forecast have the ability to forecast up to 6 to 7 month ahead [2]. The hydrological model is forcing with a range of probability in seasonal climate forecast which known as ensemble streamflow prediction (ESP) method. Previous studies have indicated that the accuracy of seasonal hydrological prediction was related to seasonal climate prediction data and watershed initial moisture condition [3] that lower skills in prediction.Wood et al. found that the largest predictability at seasonal scales are during winter where snowmelt raises soil moisture to generate runoff and streamflow is relatively slow. The smallest predictability found at the end of a climatologically dry period and preceding a wetter one that nearly all forecasts skill derives from the skill of seasonal climate prediction [4]. However, none of the previousstudiesmention the effect of SPB on hydrological forecasts. The SPB defined as the low predictability during the spring (February to May). The cause of SPB has not yet been fully understood, and various hypotheses have been still discussed to explain this phenomenon [5]. In addition, during spring (February to May) is the initial prediction time before the wet season (such as Thailand) that could help water management be more effective.

Thus, the objective of this study aims toclarify the effect of SPB, which have the evidence in a global scale, to the predictability of river discharge in CPRB and evaluate the accuracy of seasonal streamflow forecasts on each initial prediction day.

II. DATA AND METHODOLOGY

A. Experiment setting

The process to study in this paper as followed.

1) Simulate river discharge bythe hydrological model (the H08 model) using observed meteorological datafrom 1981 to 2004
2) Downscale seasonal rainfall prediction (Preprocessing).
3) Simulate river discharge by the H08 model using downscale seasonal rainfall predictionfrom 1982 to 2004
4) The river discharge results from step 3 were bias-corrected with observed river discharge (Postprocessing)
5) The river discharge results from step 1, step 3 and step 4 were compared with observed river discharge.

B. Study Area

CPRB (Fig.1), which red color indicates the high elevation and green color indicates the low elevation, is located in Thailand with a large area about 158,000 km² (30% of land area). CPRB can divide into two parts 1) Upper part and 2) Lower part. Lower part starts from NakornSawan. The lower part of CPRB flows through the central plain from NakornSawan passing Bangkok toward the Gulf of Thailand. There are two large-scale reservoirs affect to CPRB 1) Bhumibol reservoir located in Ping river and 2) Sirikit reservoir in Nan river. The observation point to represent the runoff for CPRB located in NakhonSawan city, hereafter C2 point.Fig.2 shows river discharge and rainfall in CPRB.The blue line shows the observed river discharge while the black line shows the observed river discharge excluded the effect of the reservoir, hereafter Naturalized observed river discharge. During May to October is a wet season and during November to April is dry season in this basin. The streamflow in CPRB mostlyaffected by rainfall during the wet season and like most river basin in Southeast Asia region that during winter season has no snow.

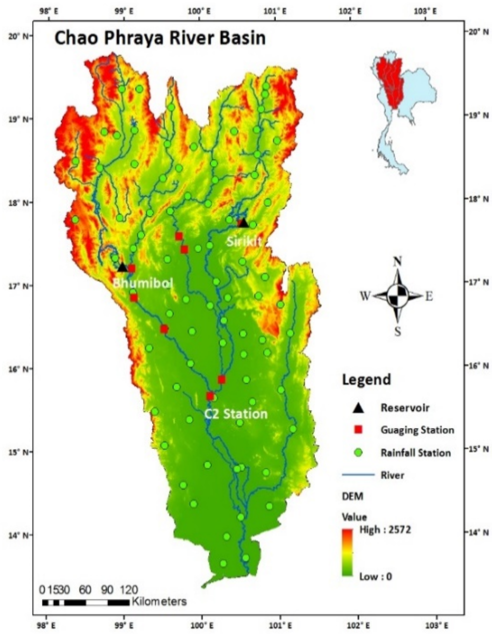


Fig. 1. CPRB and observation C2 point station

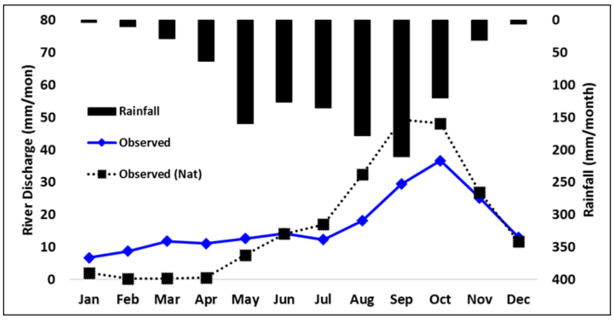


Fig. 2. Average observed river discharge and rainfall in CPRB

C. Hydrological model

A fully distributed model,the H08 model, have developed for well-organized in CPRB. Previous studies also have reproduced well in CPRB [6]. The detail of the H08 model, a distributed global water resource model, can follow in Hanasaki et al.(2008a) [7]. In this study, land surface and river modules from the H08 modelwere used. The setting of the land surface model (initial hydrological condition) and river model parameters in the H08 model followeda previous study [8]. The soil water balance was expressed as equation (1) as follow:Punctuate equations with commas or periods when they are part of a sentence, as in

$$\frac{dW}{dt} = Rainf + Q_{sm} - E - Q_s - Q_{sb} \quad (1)$$

where W is soil water content, *Rainf* is the rainfall, Q_{sm} is the snowmelt rate, E is evaporation, Q_s is a surface runoff and Q_{sb} is the subsurface runoff. The total runoff (Q_{tot}) shown in equation (2) as follows:

$$Q_{tot}=Q_s+Q_{sb} \qquad (2)$$

where Q_s is the surface runoff generated when soil water content (W) exceeds the capacity of soil water (W_f=0.15×*SD*), where *SD* is soil depth, as shown in equation (3).

$$Q_{sb}=\frac{W_f}{\tau\times 86400}\left(\frac{W}{W_f}\right)^{\gamma} \quad (3)$$

where τ and γ are two shape parameters for subsurface flow generation.

H08 was run from 1981 to 2004 which runs on a domain from 97º E to 102º E and from 13º N to 20º N. There are two simulations were carried out in this study. First, the H08 model was forced by observed meteorological dataset for calibrate model.Furthermore, details, 1981 was simulated for a spin up the initial hydrological states such as soil moisture and discharge (exclude snow since no snow in this area). Second, theH08 model was driven by seasonal rainfall prediction to validate the prediction simulation. In prediction simulation, the H08 modelwas forced by observed meteorological data except for rainfall data while seasonal rainfall prediction used as input.

D. Data

The observation data used to compare the results of river discharge from the H08 model. There are two types of inputdata in this study 1) meteorological forcing data and 2) seasonal rainfall prediction. Meteorological forcing data used for calibratingthe H08 model and bias-corrected prediction data. Seasonal rainfall prediction data used tovalidate the seasonal prediction.

1) Observed data

The observed rainfall data and observed river discharge data were used to compare the results from the H08 model in this study. Theobserved rainfall datafrom 1981 to 2004 in daily scale received from "Meteorological Department of Thailand" and "Royal Irrigation Department (RID)". The observed river discharge data at C2 station on monthly scale received from RID during 1981 to 2004. The naturalize observed river discharge (black dot line in Fig. 2) is the observed river discharge exclude the effect of the reservoir as followed from a previous study [7].

2) Meteorological forcing data

Kotsuki et al. provided a set of gridded meteorological data for CPRB, hereafter "K10" data, from 1981 to 2004 [9]. K10 is analyzed from ground observation, which ranges from 97º E to 102º E and from 13 º N to 20 º N that cover the CPRB's area. The spatial resolution of K10 data is 5 minute gridded (1/12 degree). K10 provided seven parameters as input data; 1) surface air temperature (K, 3-hourly), 2) specific humidity (kg/kg, daily), 3) surface air pressure (Pa, 3-hourly), 4) wind speed (m/s, hourly), 5) shortwave radiation (W/m², 3-hourly), 6) longwave radiation (W/m², 3-hourly), and 7) rainfall (kg/m²s¹, daily). The accuracy of rainfall from K10 data compared with ground observed station shows a good agreement in Fig. 3. However, rainfall from K10 trends to underestimate when compared with observed rainfall station that leads to underestimating in simulated river discharge when using K10 as input data.

3) Seasonal rainfall prediction

The seasonal rainfall prediction data from a previous study [10]were used in this study for two reasons. First reason, this seasonal data easy to access for utilizing. The second reason, they mentioned that their predicting system is less affected by SPB. Another reason is this seasonal rainfall prediction have been focusing on Thailand's meteorology. The available data period range from 1979 to 2011 but this study used 1982 to 2004 to simulate the river discharge from 1982 to 2004. The seasonal

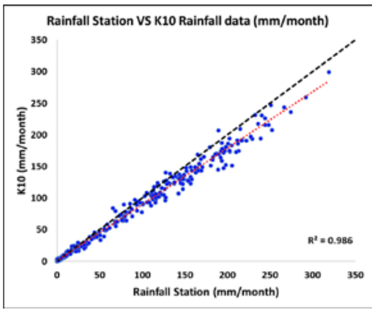
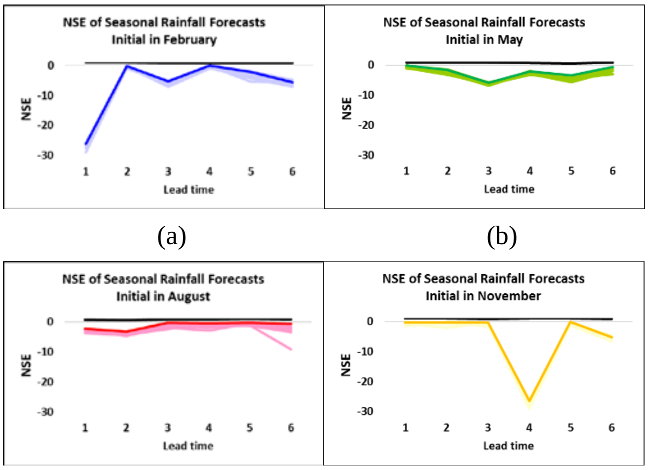


Fig. 3. Comparison between observed rainfall and K10 rainfall datain CPRB

rainfall data provided in monthly time scale with four cases about an initial day on the 1st day for prediction, 1) February 2) May 3)August and 4) November. The ability for prediction is six months ahead. As for other seasonal prediction, this seasonal data studied based on ensemble prediction systemand provide an anomaly with a reference period between 1961 and 2000.The reason for making a prediction set (or ensemble) instead of producing a single prediction because this prediction set aims to give an indication of the range of possible future states of the atmosphere. The output from this study provided eight ensembles, which difference initial condition, rainfall data. The ensemble with the different initial condition can show the range of possibilities in prediction. In this study, a seasonal rainfall prediction in anomaly was combined with Asian Precipitation Highly Resolved Observational Data Integration Towards the Evaluation of Water Resource (APHRODITE) data [11] to generate total rainfall prediction data. Seasonal rainfall prediction data was regridded with spline interpolation from 1x1º latitude and longitude grid to a 5x5 minute grid resolution. Fig. 4 shows the accuracy of raw seasonal prediction data for each initial month. Black lines show the accuracy of K10 data compared with the observed station in CPRB. Each initial month has six monthslead-time and eight-ensemble member. Overall,the accuracy of seasonal rainfall prediction is significantly lower especially during February as shown in Fig. 4a and Fig. 4d.

4) Preprocessing and postprocessing

Preprocessing and postprocessing are common in seasonal streamflow forecast, which discussed in the previous study, by taking bias correction technique to both meteorological seasonal forecasts in preprocessing and seasonal streamflow forecast in postprocessing process to remove the systematic bias of both hydrological model and climate variables [2]. This study was applied the simplest and most popular which called linear scaling method. The linear scaling method will be applied by a grid-to-grid monthly correction in this study. Linear scaling (LS), shown in equation (4), corrects the mean of the predictions based on the difference between observed (using K10 as reference data) and prediction means.



(a) (b)

(c) (d)

Fig. 4. The accuracy of raw seasonal rainfall prediction for each initial month (a) February (b) May (c) August and (d) November as initial month

$$P_{cor,d,i,j} = P_{sim,d,i,j} \times \frac{\sum_{j=1981}^{2004} P_{obs,d,i,j}}{\sum_{j=1981}^{2004} P_{sim,d,i,j}} \quad (4)$$

where P_{cor} is bias-corrected rainfall prediction or river discharge, P_{sim} is rainfall prediction or simulated river discharge, P_{obs} is observed rainfall or river discharge, i is monthly for bias correction, j is year (1981 to 2004), and d is daily for each month.

III. RESULTS AND DISCUSSION

A. Model calibration

H08 was driven by K10 data to simulated river discharge from 1981 to 2004. Fig. 5 shows the simulate river discharge results. The simulated results compared with observed river discharge and observed naturalize observed data (exclude the effect of the reservoir) at C2 station. From Fig. 5, the simulation (red line) and naturalize observed data (blue line) shows a good agreement with a high accuracy index (0.88 in NSE, 0.88 in R^2 and 4.79 mm/month in RMSE). Although, river discharge during wet season (peak) trends to underestimate with naturalizing observed data due to K10 rainfall data trends to underestimate the ground observed station. However, simulated river discharge is overestimated at some period such as 1994. The accuracy of each month simulation was discussed as shown in Fig. 6 (black line)

B. Preprocessing

Bias correction by linear scaling used for remove systematic bias for seasonal rainfall prediction using K10 as reference data from 1981 to 2004. Fig. 6 shows the result of preprocessing for each initial month from first lead month until a seventh lead month.Overall predictability was improved after bias corrected seasonal rainfall prediction data especially February and November as an initial month. The smallest predictability on February (first lead month of the initial month in February and fourth lead month of the initial month in November) were improved the accuracy. The significantpredictabilityis November and February as an initial prediction. The smallest predictability is May which beginning of the wetseason in Thailand. The accuracy of mean ensembles member trend to higher accuracy for first-month lead-time and slowlylower accuracy for longer lead-time except for initial month at August. The lower accuracy in

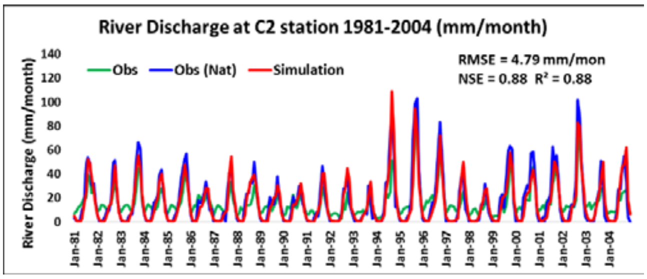
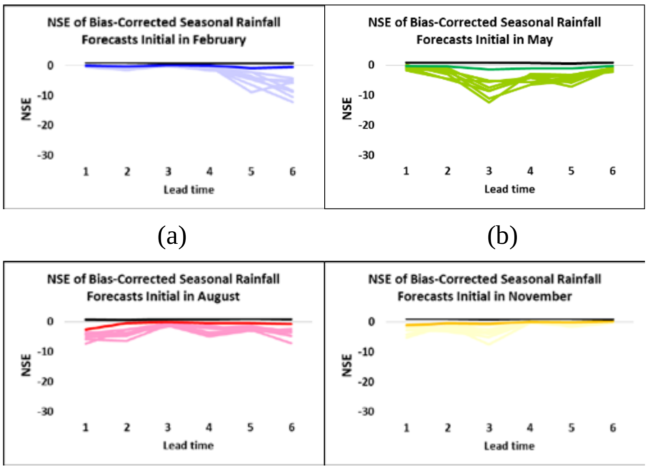


Fig. 5. Comparison between naturalize observed (blue), simulated river discharge (red) and observed river discharge (green) in monthly scale



(a) (b)

(c) (d)

Fig. 6. The accuracy of bias-corrected seasonal rainfall prediction for each initial month (a) February (b) May (c) August and (d) November as initial month

August might come from difficulty in peak prediction on the wet season (normally August is the highest rainfall intensity in CPRB).

C. River discharge prediction

After successfully bias correction of seasonal rainfall prediction in preprocessing section. The H08 model was simulated the river discharge by bias-corrected seasonal rainfall. The discharge by bias-corrected seasonal rainfall was compared the results with the gauge station at C2. Fig. 7 shows the accuracy ofriver discharge prediction.The black line shows the accuracy of river discharge simulation using K10 as input data.The results illustrate that the smallest accuracy is in February which both K10 and seasonal rainfall prediction as input data. The reason for low accuracy during February might come from the hydrological model. Soil moisture during January to April found to be low in a hydrologicalmodel that makes hydrological model hardly generate the runoff and streamflow in this case. The smallest predictability found in May as an initial month because seasonal rainfall prediction from Fig. 6 found lower in accuracy especially third-monthlead-time that lead to lower accuracy in fourth lead-month prediction in Fig. 7b. However, it is difficult to see how much difference between the accuracy of river discharge simulation using K10 as input data and seasonal rainfall data. Thus, Fig. 8 shows the difference NSE. Blue, green, red and yellow color indicates mean different the accuracy of river discharge between K10 and seasonal rainfall prediction as input data to The H08 model. Light color in Fig. 8 represents the difference accuracy of river discharge simulation for each ensemble member. The significant differences foundin May as an initial month. This large difference generated from the low accuracy of seasonal rainfall prediction during peak period (August to September).

D. Postprocessing

River discharge simulation from the previous section was bias-corrected with observed river discharge in this section.

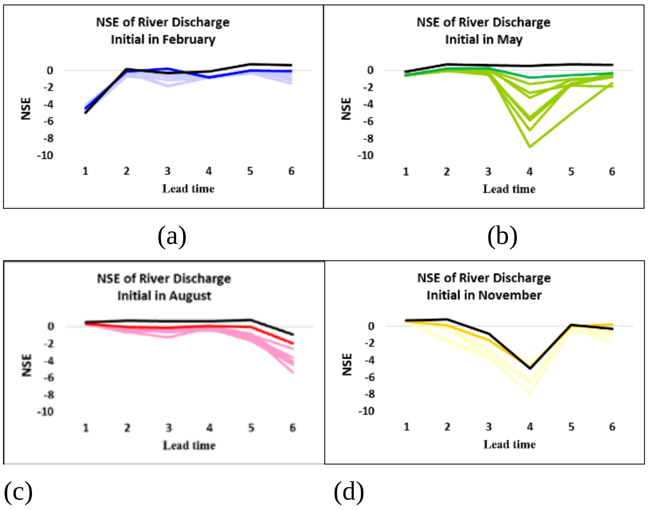


Fig. 7. The accuracy of river discharge prediction for each initial month (a) February (b) May (c) August and (d) November as initial month

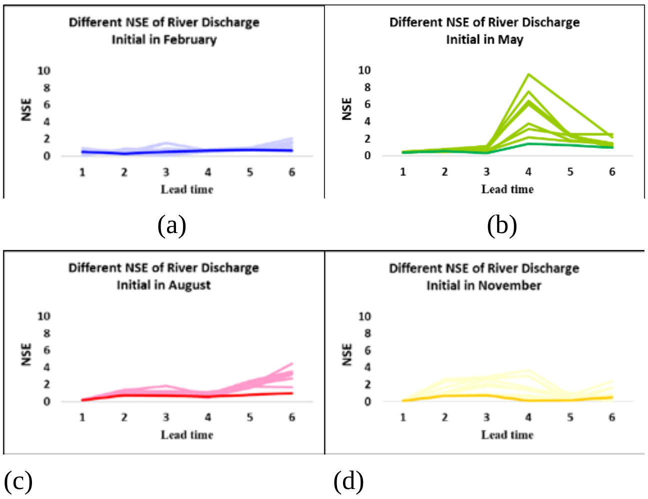


Fig. 8. Difference accuracy of river discharge prediction between K10 and seasonal rainfall prediction as input data to H08 mode for each initial month (a) February (b) May (c) August and (d) November as initial month

Bias correction by linear scaling removes monthly discharge bias for C2 station. The results of river discharge simulation from postprocessing were shown in Fig. 9. Fig. 9 is the river discharge simulation from each initial month for prediction with 1 to 3 long lead-time. The accuracy of runoff prediction was indicated by r-coefficient, RMSE and NSE as shown in Fig. 9.The horizontal axis in Fig. 9 indicates the monthly time step of the results ranges from 1982 to 2004. The vertical axis indicates river discharge in mm/month unit. River discharge prediction for the next 1 to 3 months is more accuracy than river discharge prediction for the next 4 to 6 months. Overall accuracy performance shows an agreement. However, peak river discharge at some period (ex. 1995) was lower than observed river discharge. The overall accuracy of each initial month for prediction shows in Fig. 10. Fig. 10 shows the accuracy using NSE as accuracy index. Blue, green, red and yellow color shows the accuracy of mean ensemble river discharge from eight ensembles. The results show that the overall accuracy increase after bias-corrected river discharge simulation especially the initial month for prediction at February and November.But the accuracy of May as initial month trends to increase at the 1st to 3rd lead-month before gradually lower the accuracy due to bias correction by linear scaling. The reason that the accuracy of May as an initial month on the 4th lead month drops was due to linear scaling method cannot remove bias for peak river discharge. In another word, linear scaling by remove bias using mean difference cannot remove bias for the peak. The most predictability found in August and November as the initial month that slowly lower accuracy when time pass. The output of each initial month illustrate in hydrograph is shown in Fig. 11. Initial month in each graph has a range only six months for each year such as Fig. 11a shows the output of river discharge from February to July range from 1982 to 2004, Fig. 11b shows the output of river discharge from May to October for each year. The most predictability is November as an initialmonth;second most predictability is August as an initial month while the less predictability is May as an initial month.

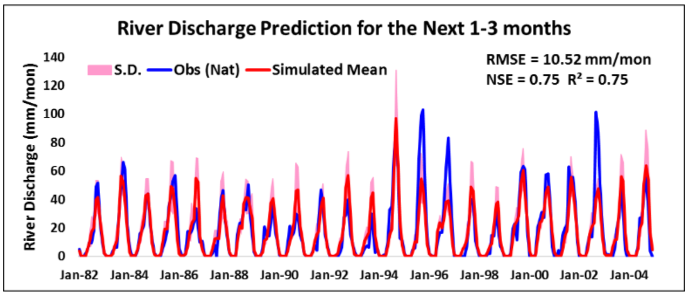
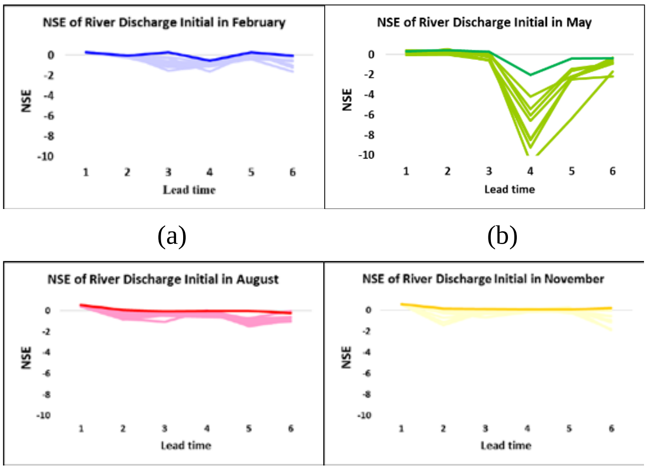


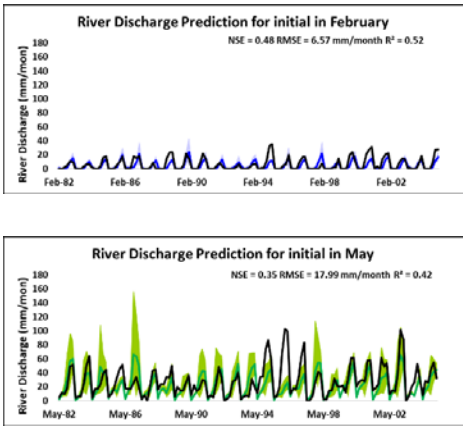
Fig. 9. River discharge simulation using bias-corrected rainfall prediction of 1 to 3 months lead time as input data from 1982 to 2004.



(a) (b)

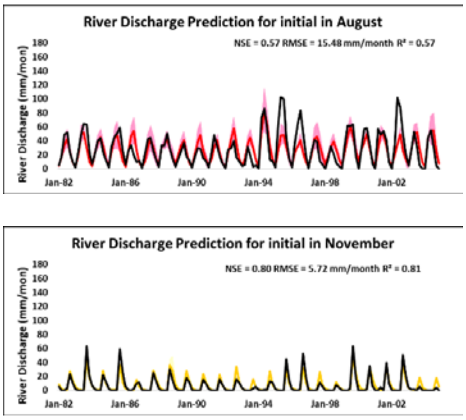
(c) (d)

Fig. 10. The accuracy of river discharge simulation using bias-corrected rainfall as input after postprocessing (a) February (b) May (c) August and (d) November as an initial month for prediction



(a)

(b)



(c)

(d)

Fig. 11. River discharge simulation for each initial month

IV. CONCLUSION

In this study, we found that river discharge prediction based on a hydrological model using bias-corrected seasonal rainfall prediction by linear scaling methodcan predict the monthly river discharge in CPRB with acceptable accuracy as r coefficient, RMSE and NSE index shown in Fig. 9. The results ofthe accuracy of the next 1 to 3 months in river discharge prediction were better in accuracy than river discharge prediction for the next 4 to 6 months. We found that the effect of SPB on rainfall prediction shows less predictability on May that effected on lower river discharge prediction skills during spring, which initial day for prediction is the first day of February and May. On the other hand, the river discharge prediction skills were shown better results for the initial day for prediction of first August and November due to rainfall prediction are better in accuracy. Thus, its conclusion that the river discharge prediction from the hydrological model for the initial day for prediction in August and November are better than prediction in February and May. We also found that bias between observed river discharge and simulated river discharge arise from the H08 model and rainfall prediction. Therefore, a study of prediction rainfall and SPB is important for river discharge prediction especially during the transitional time (end of dry season to wet season).Future study on rainfall prediction can be developed to compare the river discharge prediction skills by current dynamical seasonal rainfall prediction. Together with the hydrologicalmodel developing and rainfall prediction will give a lot of benefit for water management in Thailand.

APPENDIX

Nash-Sutcliffe model efficiency coefficient (NSE) used to indicate the accuracy (predictive power) between observed data and simulated data of hydrological model. NSE can range from -∞ to 1 which an efficiency of 1 means perfect match between simulated discharge and observed data. NSE equals to 0 indicates that the model predictions are accurate as the mean of observed data where below 0 means the observed mean is better predictor than the model. The equation of NSE shows as equation (5).

$$NSE = 1 - \frac{\sum_{t=1}^{T}(Q_m^t - Q_o^t)^2}{\sum_{t=1}^{T}(Q_o^t - \overline{Q_o})^2} \quad (5)$$

whereQ_m^t is model data, Q_o^t is observeddata and $\overline{Q_o}$ is average value of observed data.

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