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Seasonal Streamflow Forecasts Based On Physical-Based Model for Chao Phraya River Basin in Thailand

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Outline

- Introduction
 - Problem
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- Data and Methodology
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- Results and discussion
- Conclusion



Bhumibol Dam



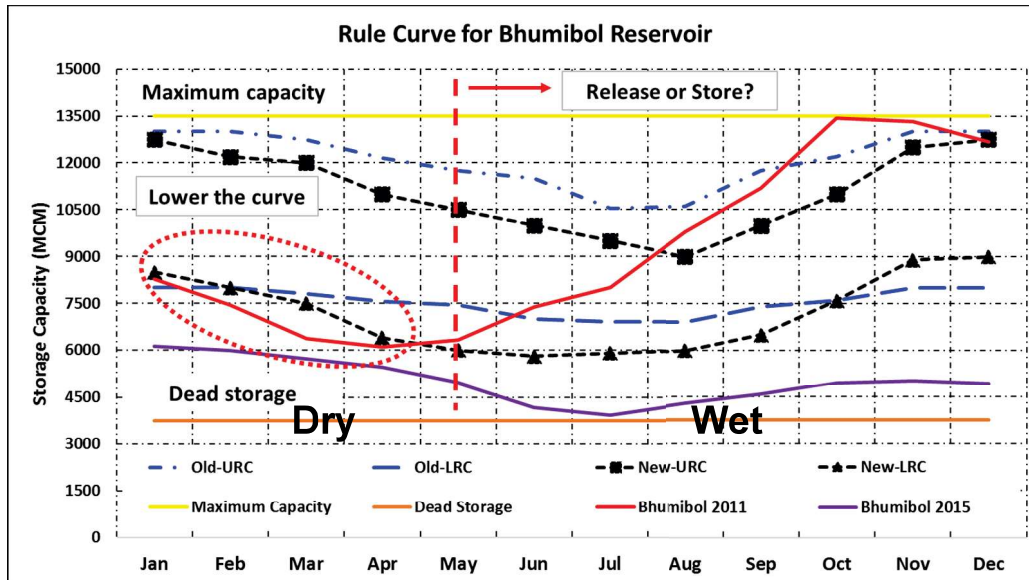
Sirikit Dam

Introduction

➤ Problem

- Thailand's water management
- Rule curve
- Difficulty in water management
- Seasonal forecast
- Transition season

Thailand Water Management



Old Rule Curve
New Rule Curve

2011 2015

Source: EGAT

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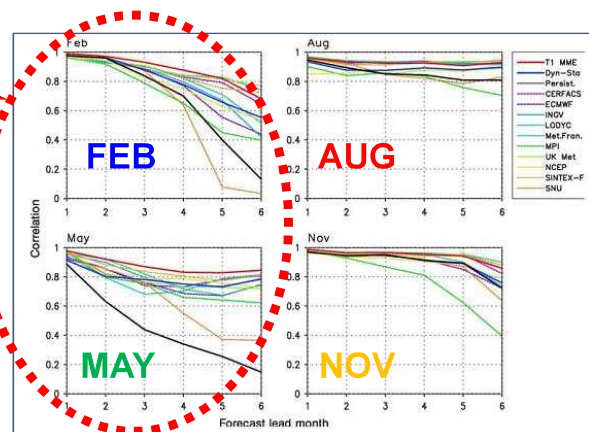
Introduction

➤ Previous studies

- A hydrological model is forcing with a range of probability in seasonal climate forecast (ensemble streamflow prediction; **ESP**)
- Wood et al. 2016 indicated the predictability of streamflow prediction.
- The most predictability at seasonal scales are **during winter**
- The smallest predictability found at the **end of a climatologically** (dry → wet)

Spring Predictability Barrier (SPB)

Prediction skill is **lower**



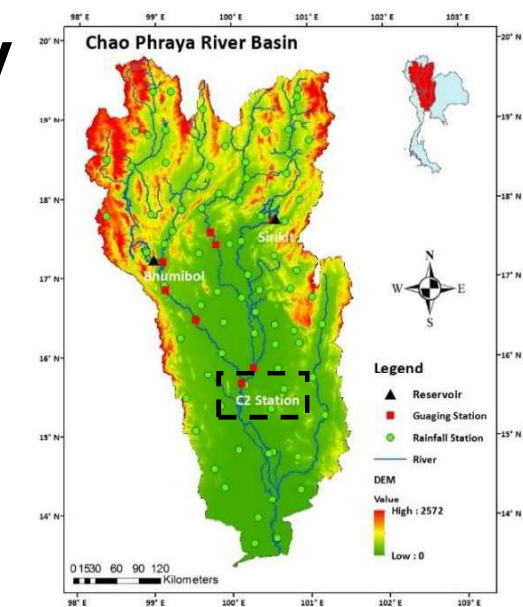
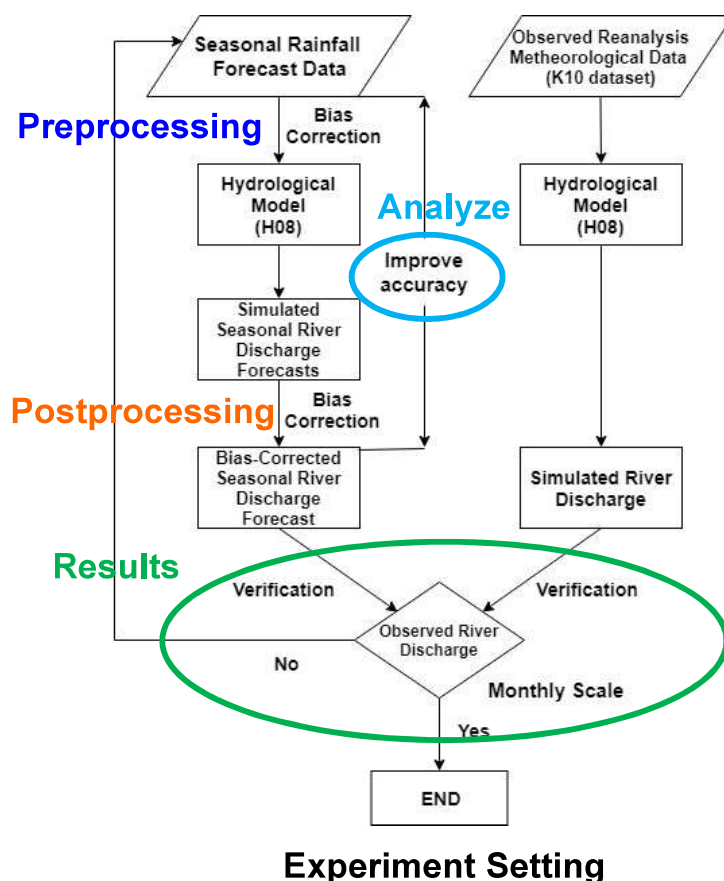
Jin et al. 2008⁴

Objective

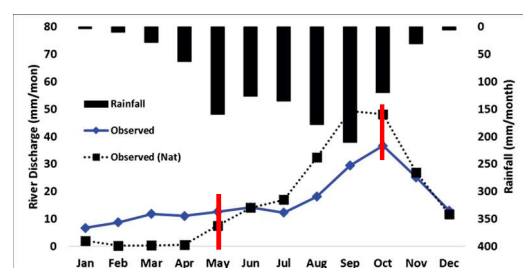
- Clarify the effect of SPB, which have the evidence in a global scale, to the predictability of river discharge in Chao Phraya River Basin (CPRB)
- Evaluate the accuracy of seasonal streamflow forecasts on each initial prediction day

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Data and Methodology



Dry and Wet Season



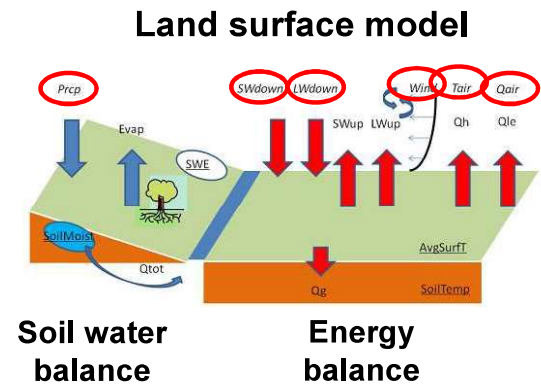
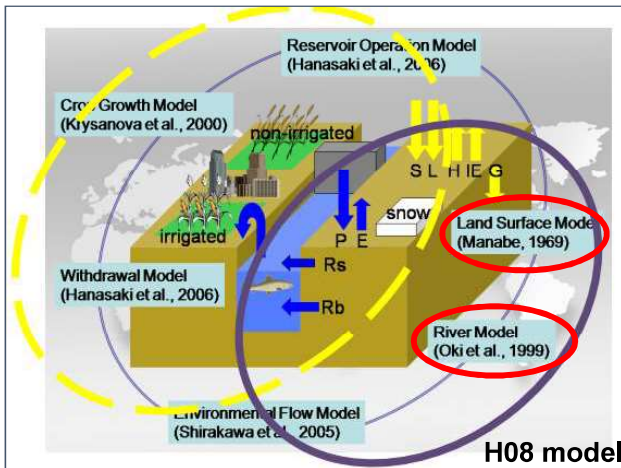
Study area

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Data and Methodology

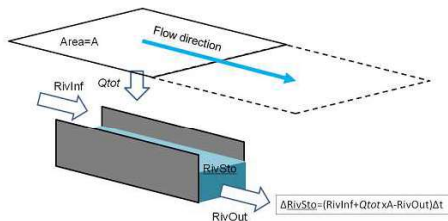
➤ Hydrological model

Model was developed by Hanasaki et al. 2008a



$$\text{Soil water balance } \frac{dW}{dt} = Rainf + Q_{sm} - E - Q_s - Q_{sb}$$

$$\text{Energy balance } (1 - \alpha)SW^{\downarrow} + LW^{\downarrow} = \sigma T_s^4 + \epsilon E + H + G$$



River model

$$\Delta RivSto = (RivInf + Q_{tot}A - RivOut)\Delta t$$

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Data and Methodology

➤ Data

• Observed data

- Rainfall data (1981-2004)

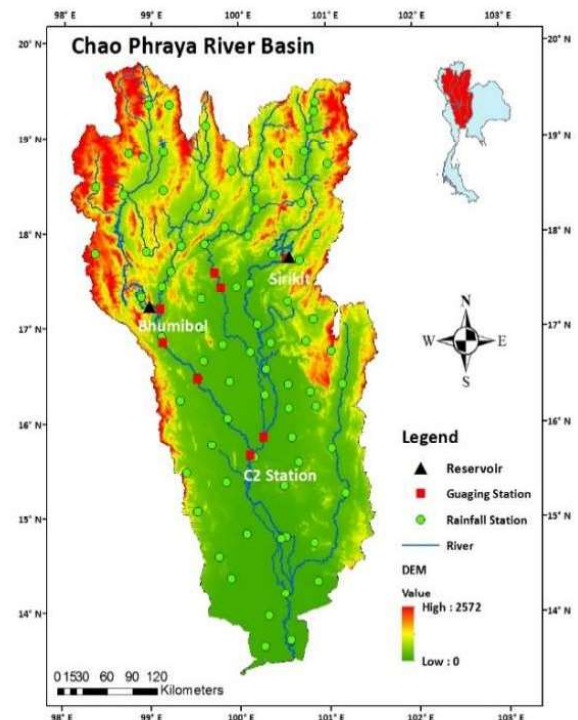
Thai Meteorological Department (TMD)

Royal Irrigation Department (RID)

- River discharge data at C2 station

Royal Irrigation Department (RID)

- Rainfall Station
- Gauging Station
- ▲ Gauging Station



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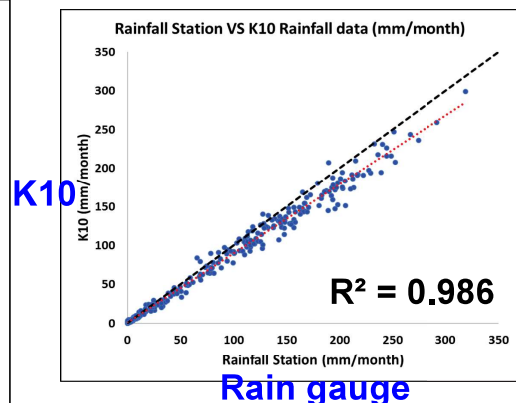
Data and Methodology

- Meteorological forcing data

- Kotsuki et al. 2010 provide a set of meteorological data (K10)
- Developed from rain gauge station in CPRB
- Several study used K10 as input data

Data period: 1981-2004

- ✓ Surface air temperature (3-hourly)
- ✓ Specific humidity (daily)
- ✓ Surface air pressure (1-hourly)
- ✓ Wind speed (1-hourly)
- ✓ Shortwave radiation (3-hourly)
- ✓ Longwave radiation (3-hourly)
- ✓ Precipitation (daily)
- ✓ Data resolution : 5 min. grid resolution



Comparison between observed rainfall and K10 rainfall data in CPRB

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Data and Methodology

- Seasonal Rainfall Prediction (Imada et al. 2015)

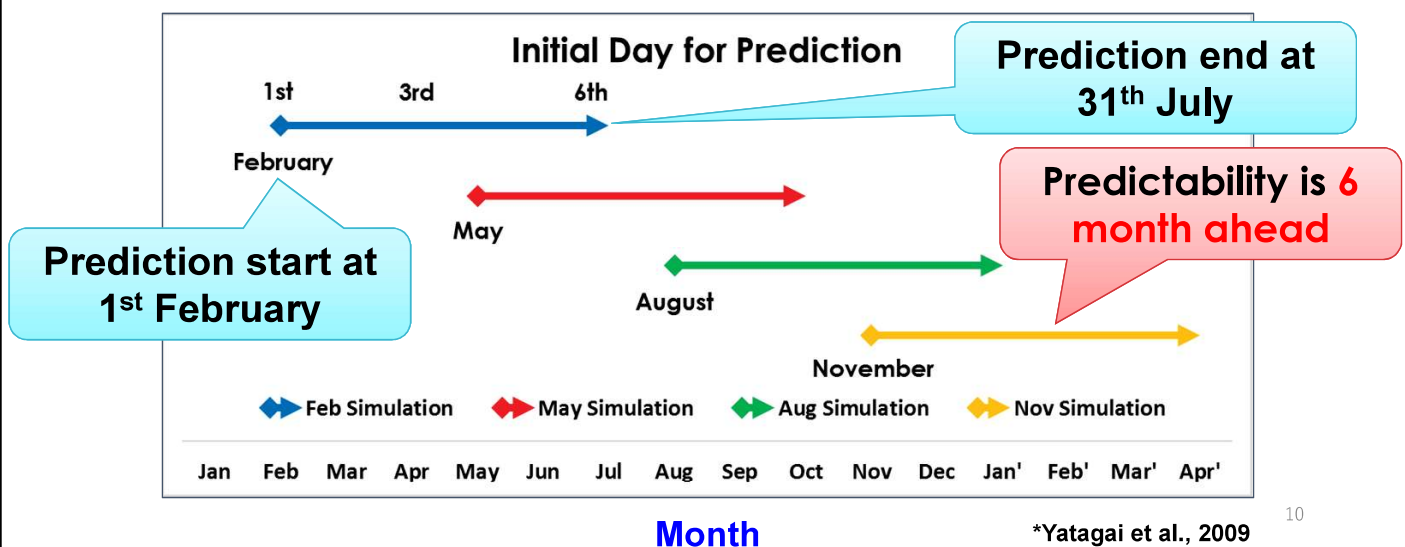
- Easy to access for utilizing
- Focused in Thailand's meteorological

Data period: 1979-2011

- Anomaly Precipitation (Ref.year 1961-2000; monthly time scale)
- 8 Ensembles

Downscaling 1.4 degree to 5 min resolution

**Rainfall =
APHRODITE* +
Anomaly**



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Data and Methodology

➤ Methodology

- Preprocessing and postprocessing

Taking bias correction techniques to remove the systematic bias of both hydrological model and climate variables

Linear scaling (LS)

- Grid-to-grid monthly correction
- Corrected mean value between model and observed

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

cor = bias-corrected data

obs = observed data

sim = simulated data

i = month (Jan, Feb,..., Dec)

j = year (1981, 1983,..., 2004)

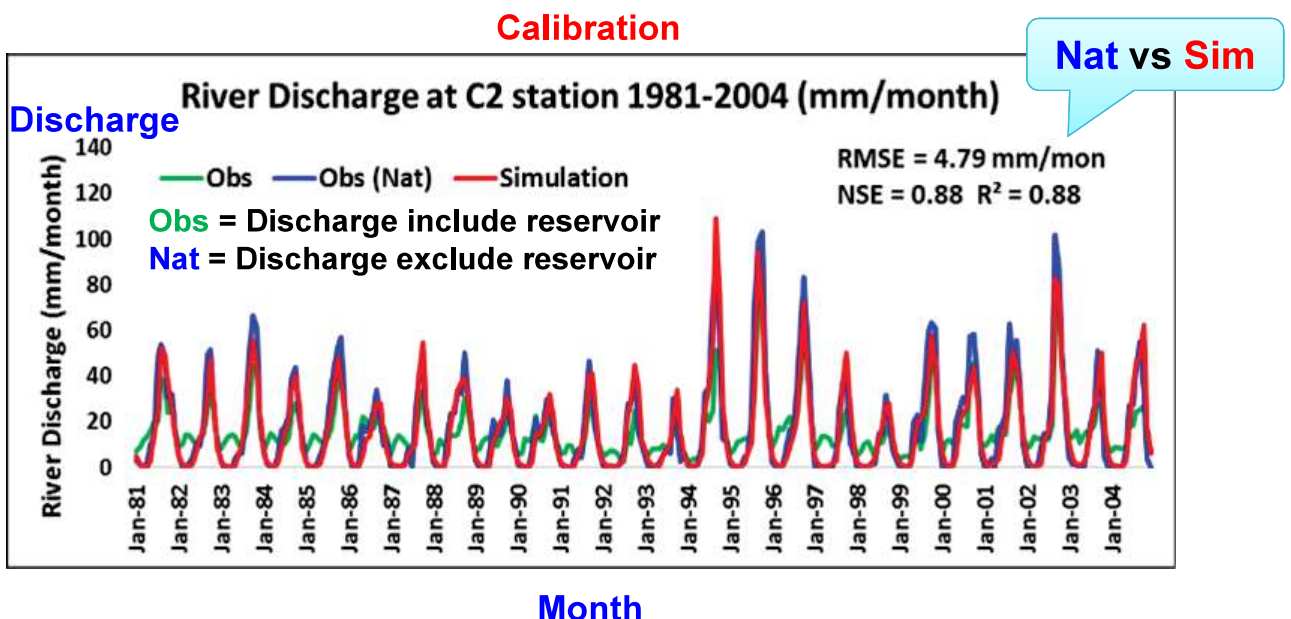
d = day (1,2,3,4,5...31 or 30 or 28 or 29)

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Results and discussion

- Model Calibration

- H08 was driven by K10 data to simulated river discharge from 1981 to 2004



Overall, The river discharge simulation by K10 data shows a good results

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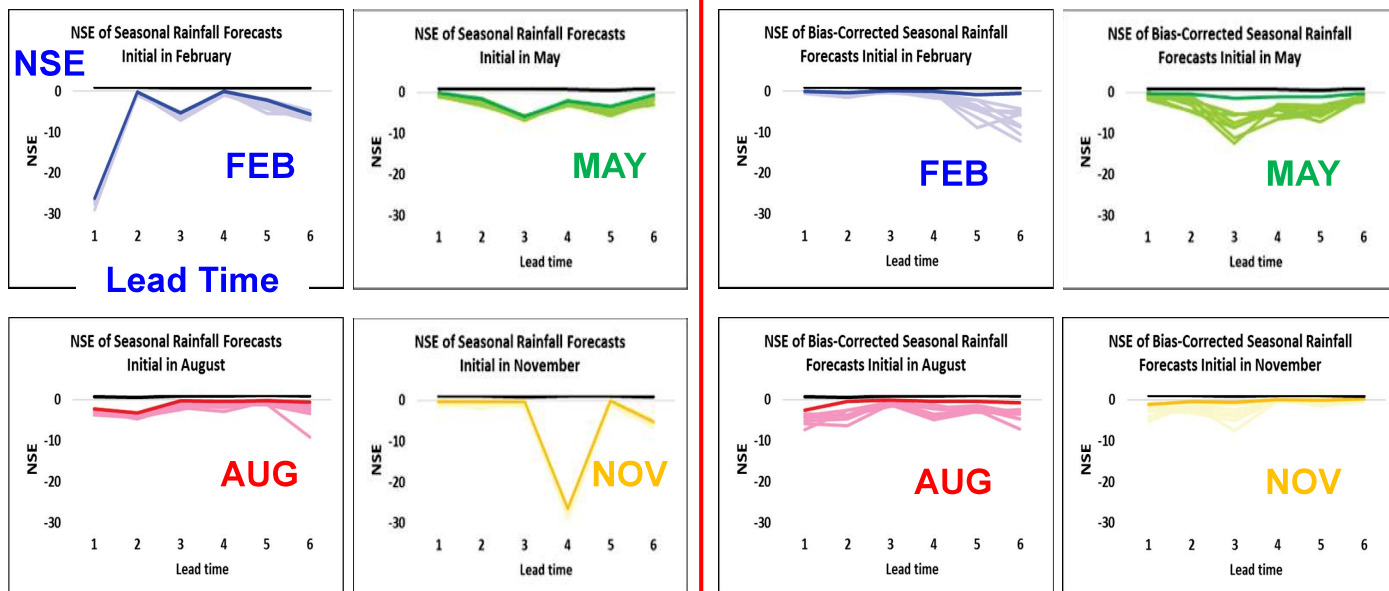
Results and discussion

- Preprocessing (Bias correction of rainfall prediction)
 - Remove bias from seasonal rainfall prediction (Linear Scaling)

RAW

Bias Correction

Preprocessing



NSE, range from $-\infty$ to 1

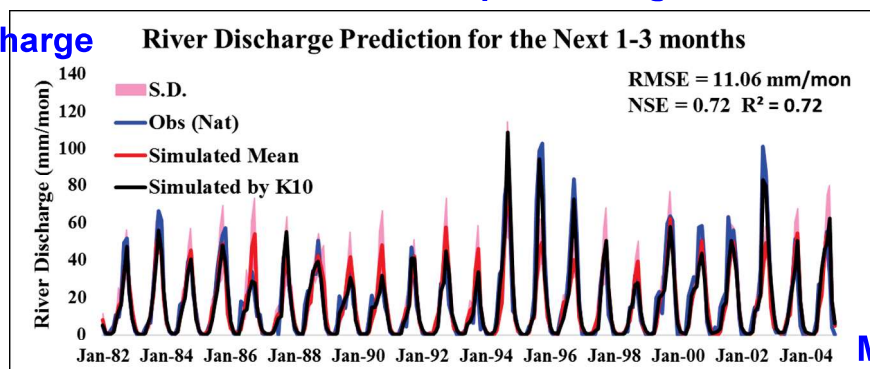
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Results and discussion

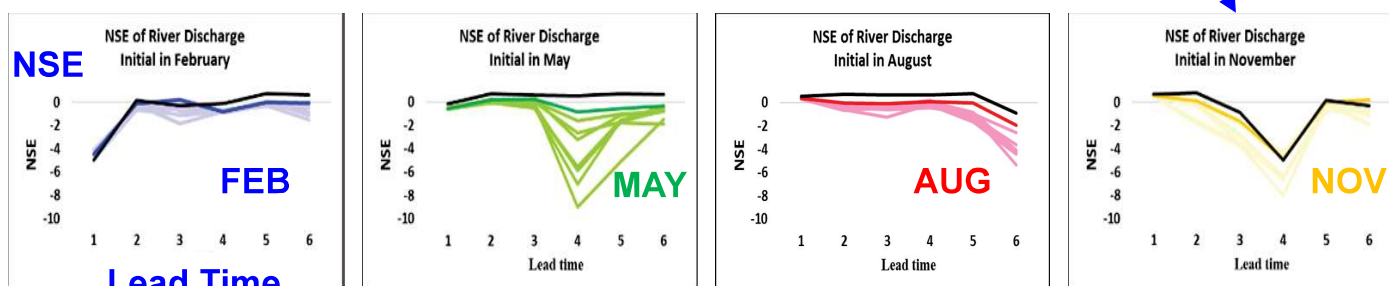
- River discharge simulation
 - H08 model was simulated by bias-corrected rainfall prediction

Prediction - Preprocessing

Discharge



— Obs vs Sim K10
 Color lines Obs vs Mean
 Light color Sim BS-rainfall
 Obs vs Ensemble Sim BS-rainfall



— NSE, K10 Sim

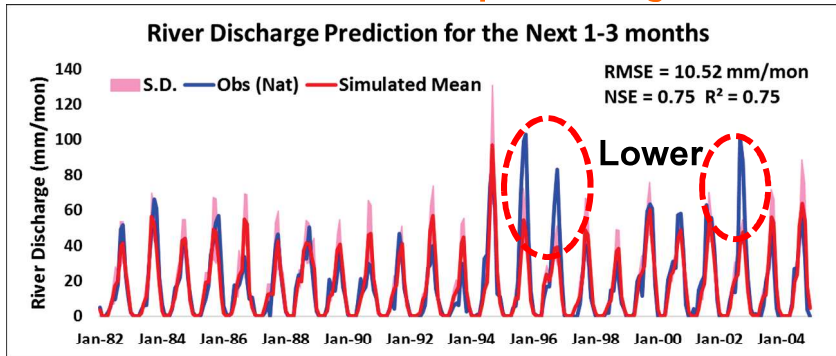
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Results and discussion

- Postprocessing

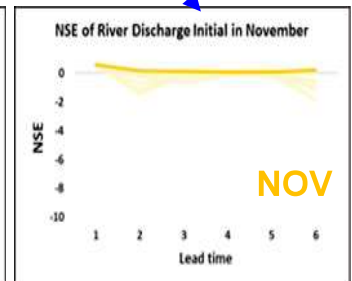
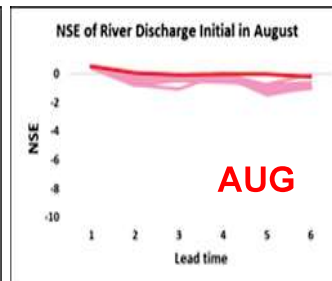
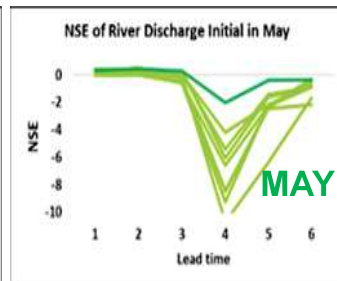
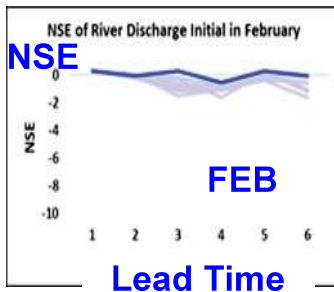
- Bias-corrected river discharge simulation from last slide

Prediction - Postprocessing



BS Discharge with Obs

Color lines
Obs vs Mean
Sim BS-rainfall
Light color
Obs vs Ensemble
Sim BS-rainfall



NSE, range from $-\infty$ to 1 Bias correction fix mean of data but not peak

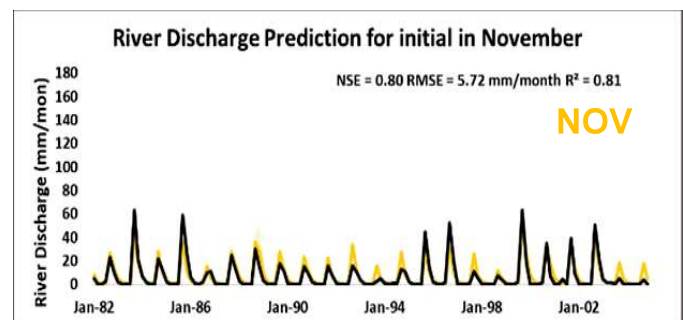
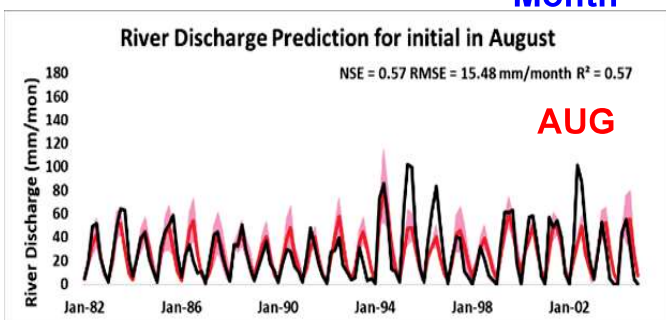
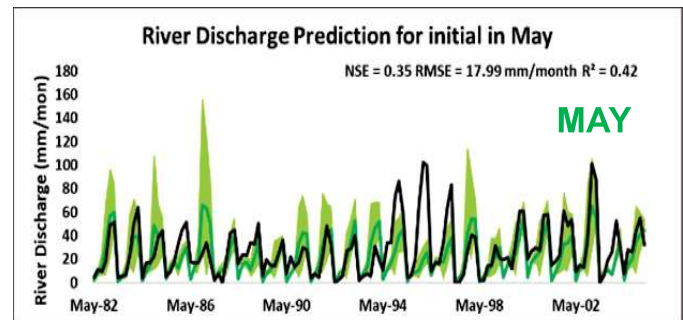
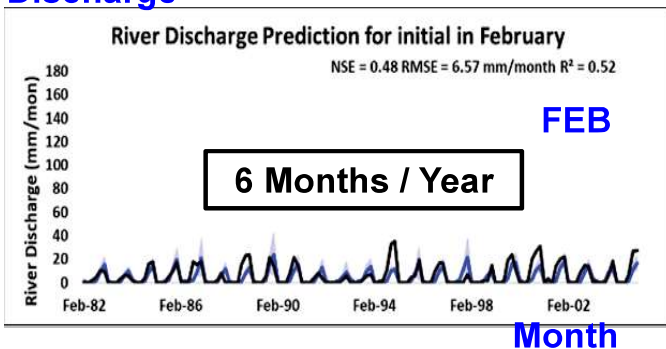
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Results and discussion

- Postprocessing

- River discharge simulation for each initial month

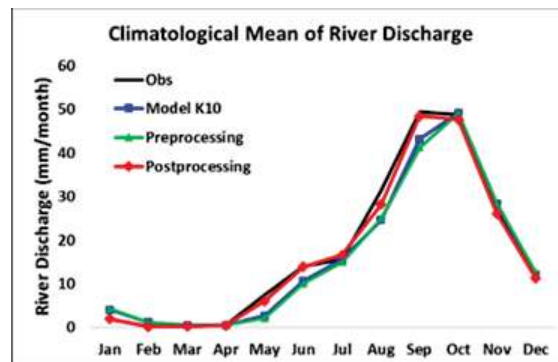
Discharge



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Conclusion

- The results of the 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
- Bias Correction fix mean of data

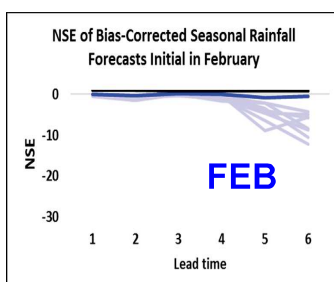


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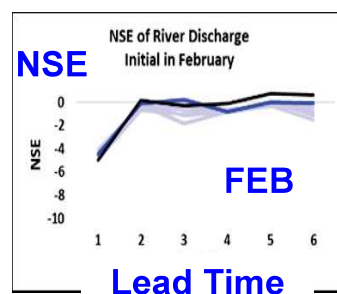
Conclusion

- 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)

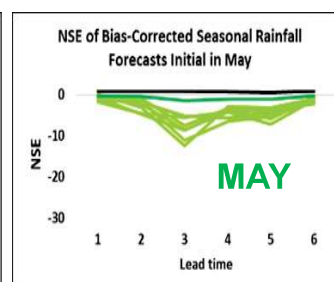
BS rainfall



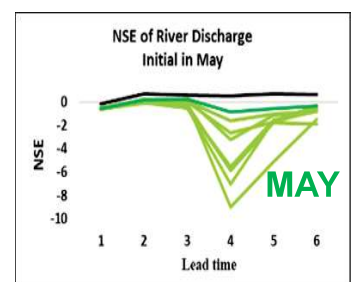
River Discharge



BS rainfall



River Discharge



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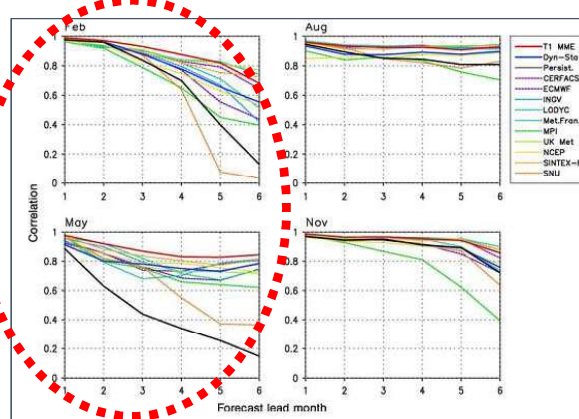
THANK YOU FOR YOUR ATTENTION

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Introduction

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

Prediction skill is lower



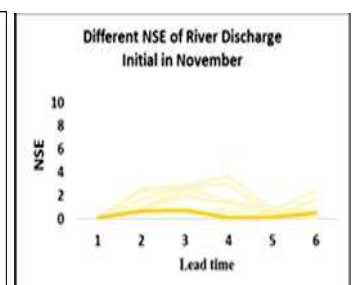
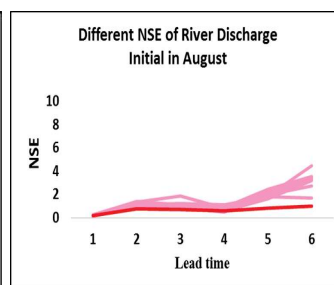
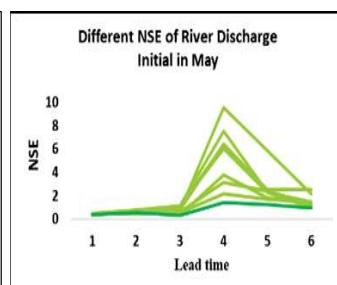
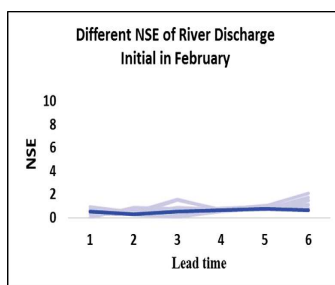
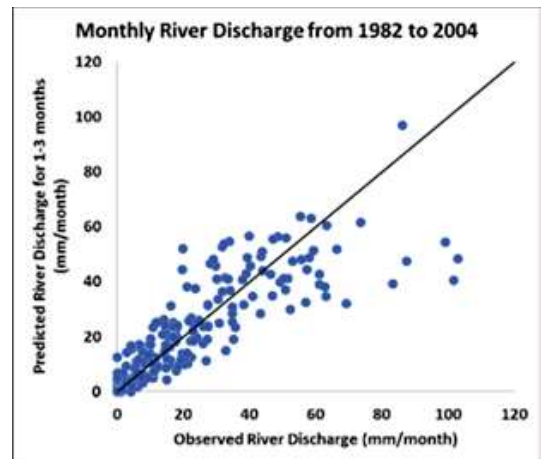
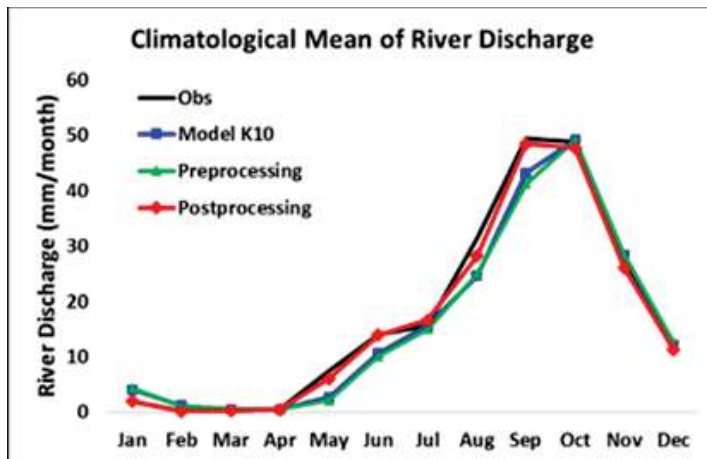
Jin et al. 2008

➤ Objective

- Clarify the effect of SPB, which have the evidence in a global scale, to the predictability of river discharge in CPRB
- Evaluate the accuracy of seasonal streamflow forecasts on each initial prediction day

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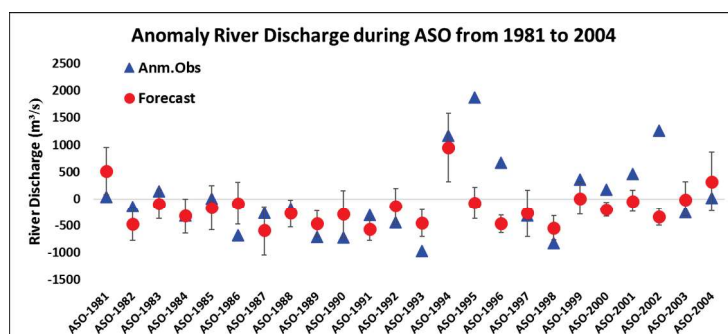
Results and discussion



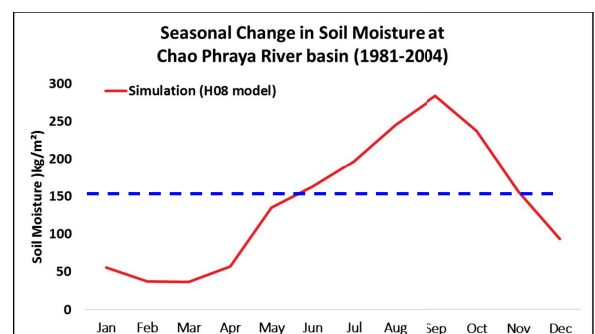
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Results and discussion

Average during August, September and October



Average soil moisture



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➤ Nash-Sutcliffe model efficiency coefficient (NSE)

Nash-Sutcliffe model efficiency coefficient (NSE) used to indicate the accuracy (predictive power) between observed data and simulated data of the hydrological model. NSE can range from $-\infty$ to 1 which an efficiency of 1 means a 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 a better predictor than the model.

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

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