



Bhumipol Dam Operation Improvement via smart system for the Thor Tong Daeng Irrigation Project, Ping River Basin, Thailand

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Introduction

- Up to now the dam operation is operated under the past record based rules.
- In the drought year, water storage in the Bhumipol Dam is inadequate to allocate water for agriculture, and caused water deficit in many irrigation projects. Farmers need to find extra sources of water such as water from farm pond or groundwater as a supplement. The operation of Bhumipol Dam and irrigation demand estimation are vital for irrigation water allocation to help solve water shortage issue in the irrigation project.

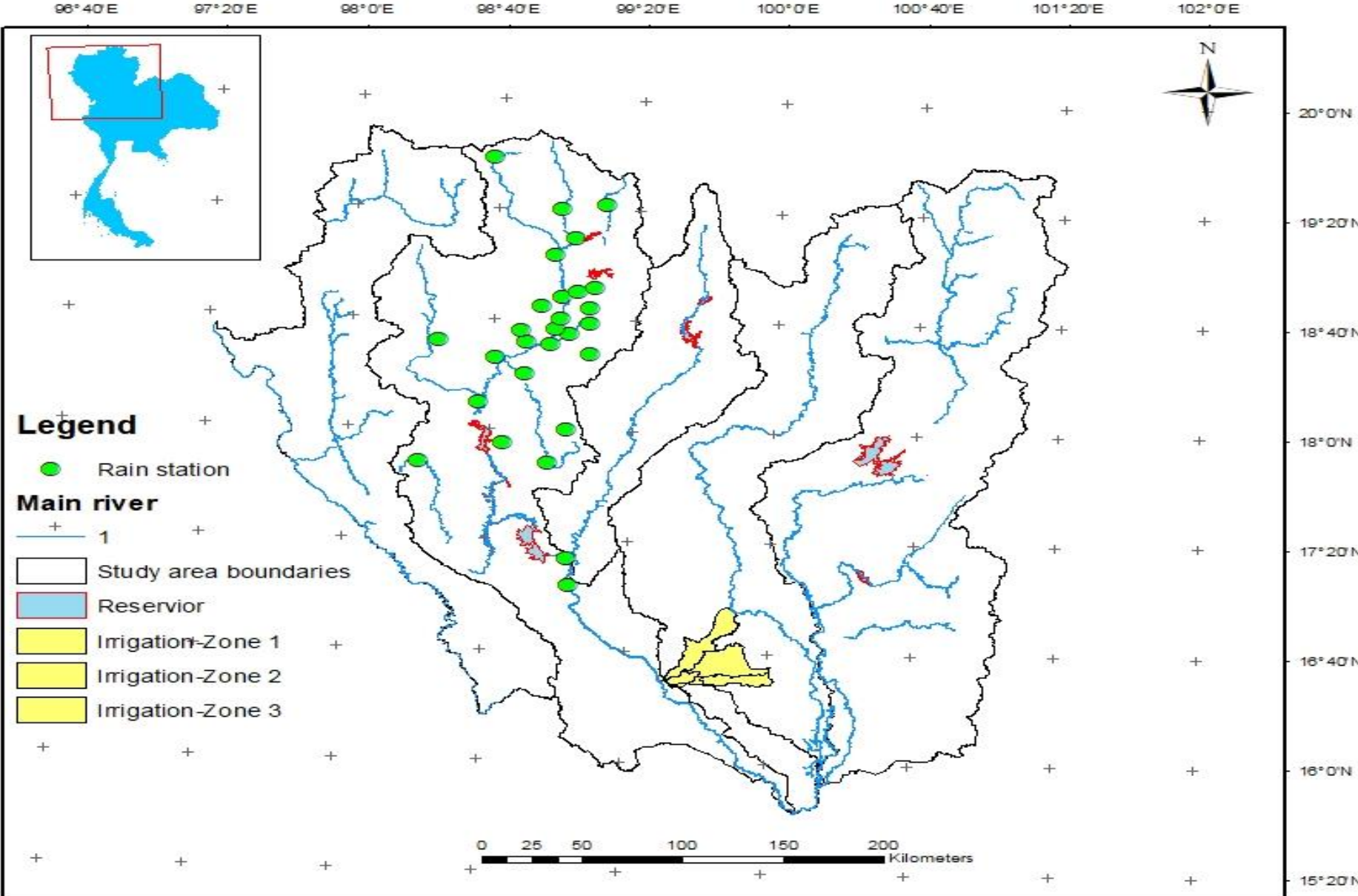
objectives

- The study aims to determine the smart dam operation system to mitigate water shortage in the irrigation project (Thor Thong Daeng) via introduction of machine learning to improve dam operation (**inflow and release**) and **irrigation demand** estimation via soil moisture estimation from satellite images

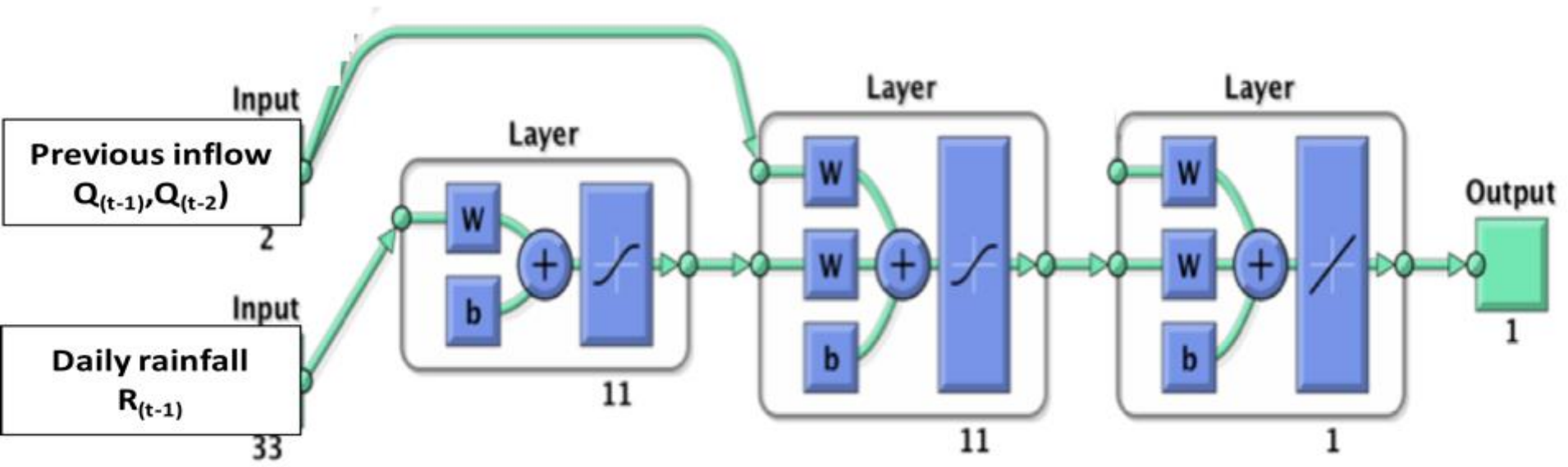
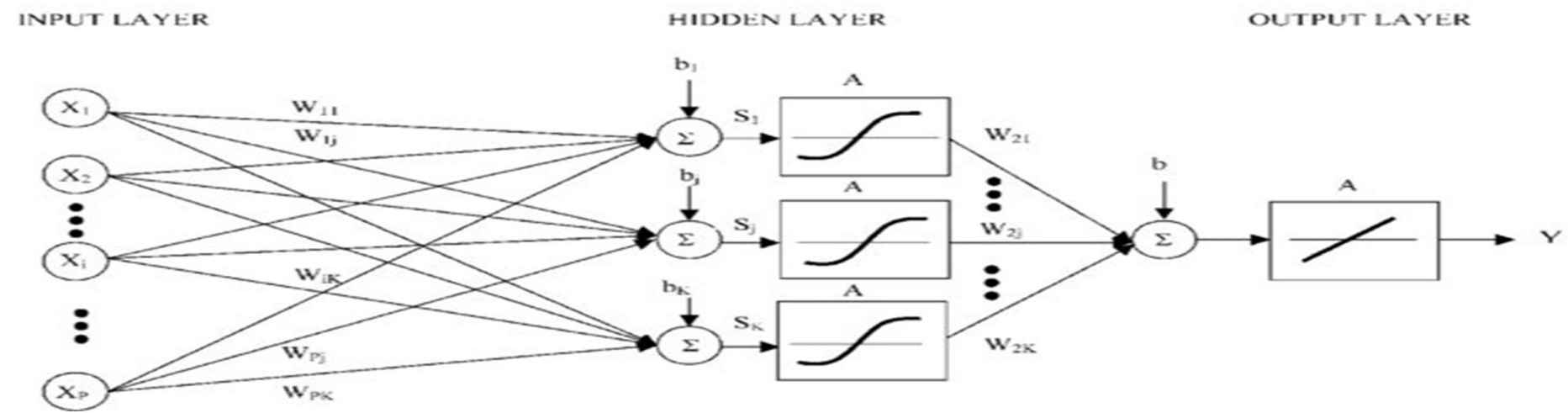
Study area

- **Bhumipol Dam** is a major storage dam in the Central Plain and provide water for irrigation and water supply including Bangkok (storage 13,462 million cubic meters, 154 m height)
- **The Tor Tong Daeng Irrigation Project** with the irrigation area of 61,400 hectares is located in the Ping Basin of the Upper Central Plain of Thailand where farmers depended on both surface water and groundwater.

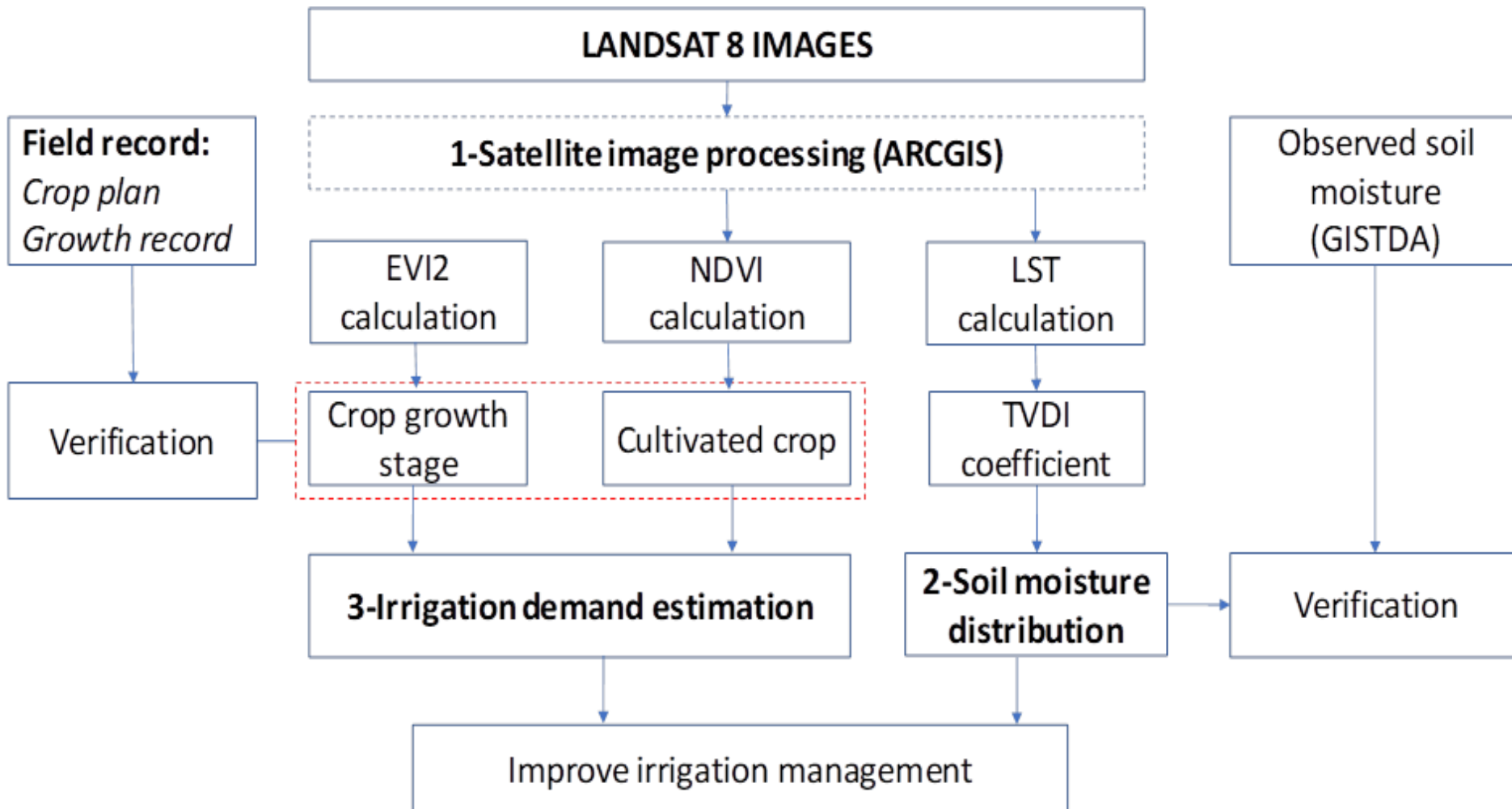
Study area



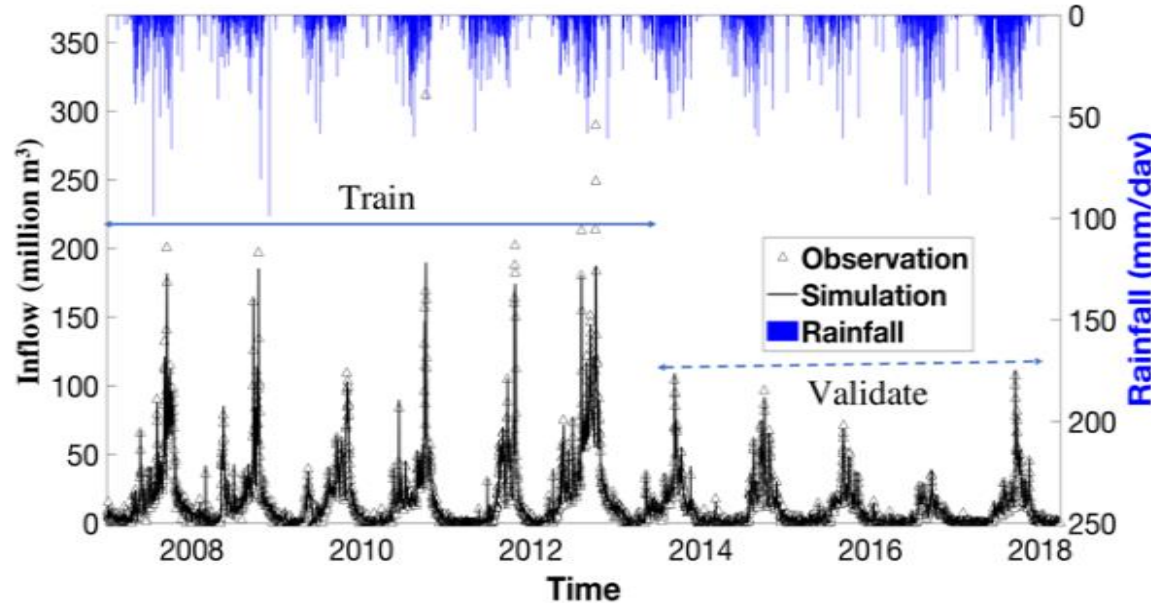
Structure of ANN with conveniently input layer for rainfall-runoff for extreme estimation



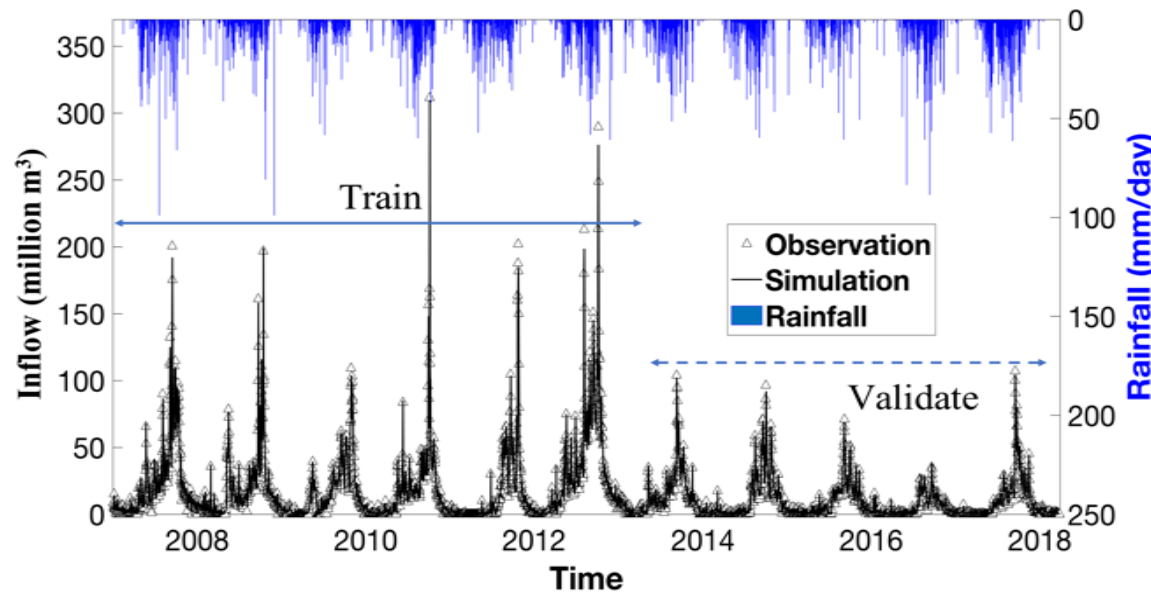
Frame work of the demand study



Results



a) Without conveniently input layer (normal)

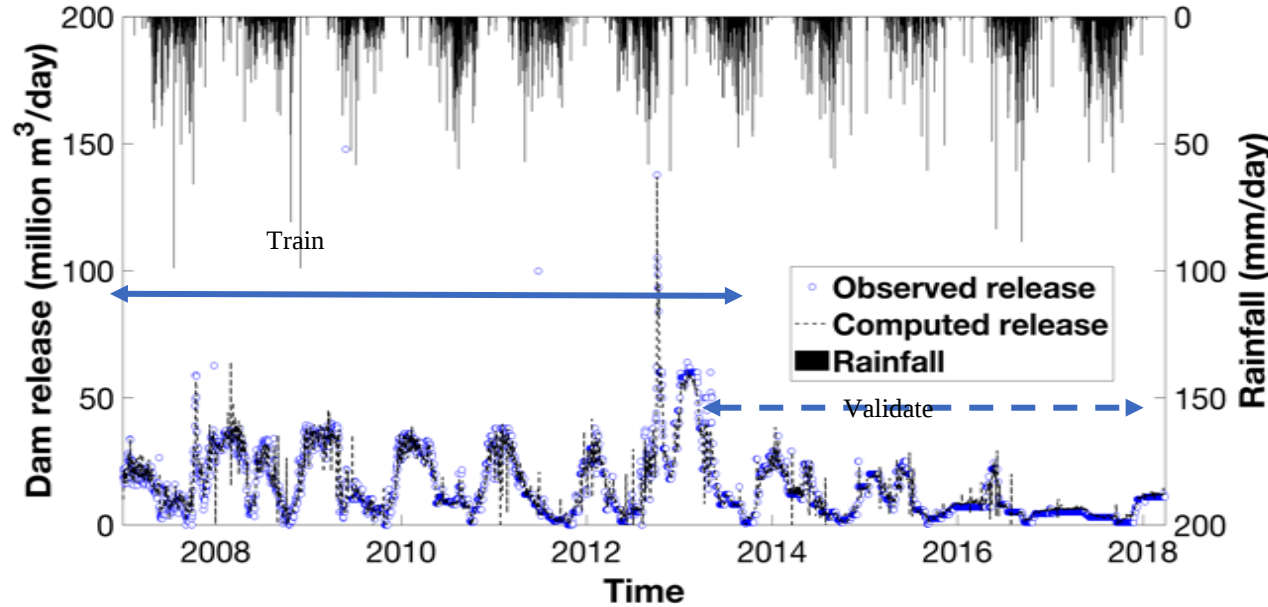


b) with conveniently input layer (cover extreme)

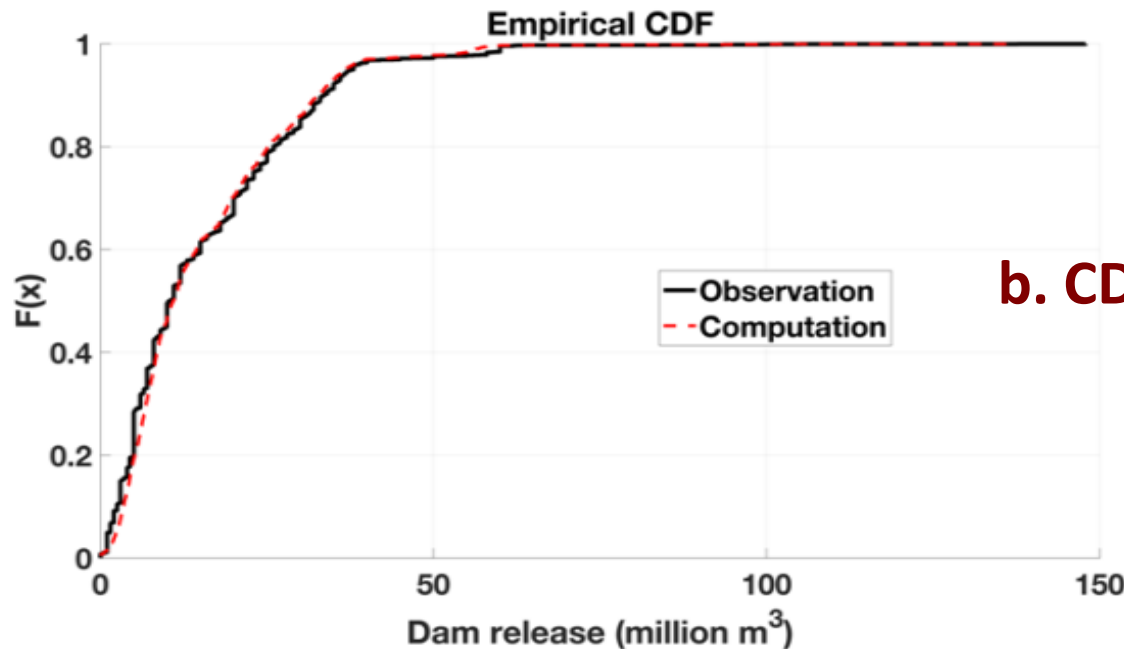
Performance of the ANN model for dam inflow estimation

Structure	C1		C2		C3		C4		C5		C6	
	$R_{(t-1)}, I_{(t-1)}$		$R_{(t-1)}, MR_{(30days)}$		$R_{(t-1)}, I_{(t-1)}, I_{(t-2)}$		$R_{(t-1)}, R_{(t-2)}, I_{(t-1)}, I_{(t-2)}$		$R_{(t-1)}, MR_{(30 days)}, I_{(t-1)}, Q_{(t-2)}$		$R_{(t-1)}, R_{(t-2)}, MR_{(30 days)}, I_{(t-1)}$	
Activate function	Tanlog	Sinlog	Tanlog	Sinlog	Tanlog	Sinlog	Tanlog	Sinlog	Tanlog	Sinlog	Tanlog	Sinlog
Hidden neutron	9	3	8	23	14	5	3	8	5	3	3	13
Epoch	15	39	30	34	9	12	19	25	20	40	21	18
RMSE_train	8.249	7.99	7.809	8.454	6.994	8.226	7.265	8.032	7.79	8.046	8.036	6.39
R^2	0.889	0.9	0.906	0.887	0.926	0.9	0.92	0.907	0.903	0.898	0.898	0.94
RMSE_val	6.219	5.753	11.59	11.82	6.007	5.944	6.511	6.248	6.38	6.417	6.59	7.84
R^2	0.932	0.935	0.707	0.737	0.9	0.928	0.894	0.904	0.921	0.929	0.932	0.92

Performance dam release simulation



a. dam release in time series

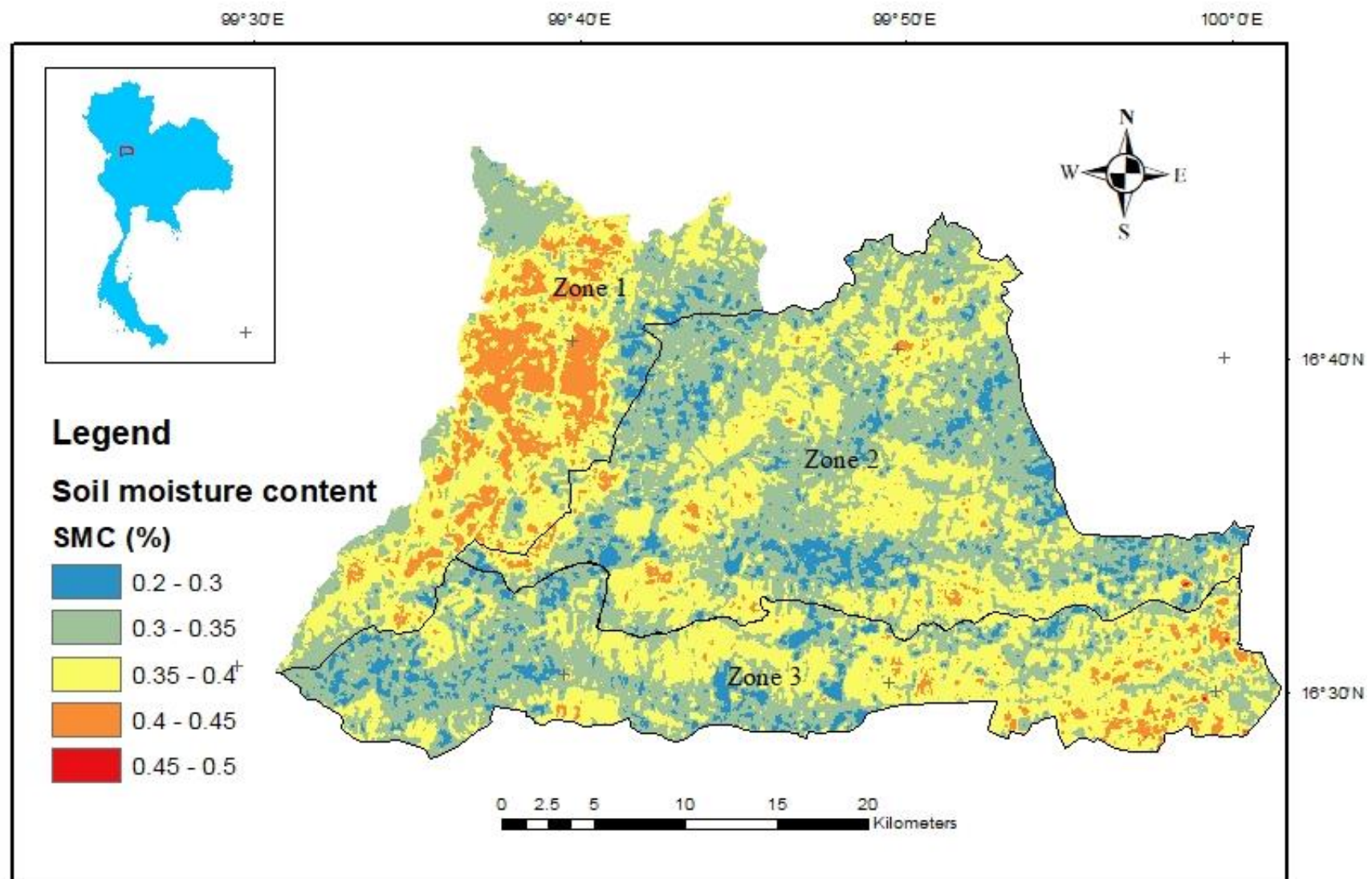


b. CDF curve of dam release

Performance of the ANN model for dam release estimation

Structure	D1		D2		D3		D4		D5		C6	
	$C_{(t-1)}, I_{(t-1)}$		$R_{(t-1)}, C_{(t-1)}, I_{(t-1)}$		$R_{(t-1)}, C_{(t-1)}, C_{(t-2)}, I_{(t-1)}$		$R_{(t-1)}, C_{(t-1)}, I_{(t-1)}, I_{(t-2)}$		$C_{(t-1)}, C_{(t-2)}, I_{(t-1)}, I_{(t-2)}$		$R_{(t-1)}, C_{(t-1)}, C_{(t-2)}, I_{(t-1)}, I_{(t-2)}$	
Activate function	Tanlog	Sinlog	Tanlog	Sinlog	Tanlog	Sinlog	Tanlog	Sinlog	Tanlog	Sinlog	Tanlog	Sinlog
Hidden neutron	20	24	24	6	3	19	4	29	4	11	10	5
Epoch	80	14	20	22	84	26	15	18	146	113	22	43
RMSE_train	7.863	8.07	8.437	9.028	6.366	5.429	8.418	6.558	5.33	5.662	4.809	5.1
R ²	0.673	0.655	0.633	0.583	0.792	0.83	0.631	0.773	0.92	0.829	0.967	0.86
RMSE_val	6.93	7.037	7.909	7.485	4.627	4.564	7.756	7.756	3.912	4.104	6.722	5.04
R ²	0.702	0.671	0.586	0.65	0.86	0.884	0.61	0.64	0.958	0.903	0.892	0.87

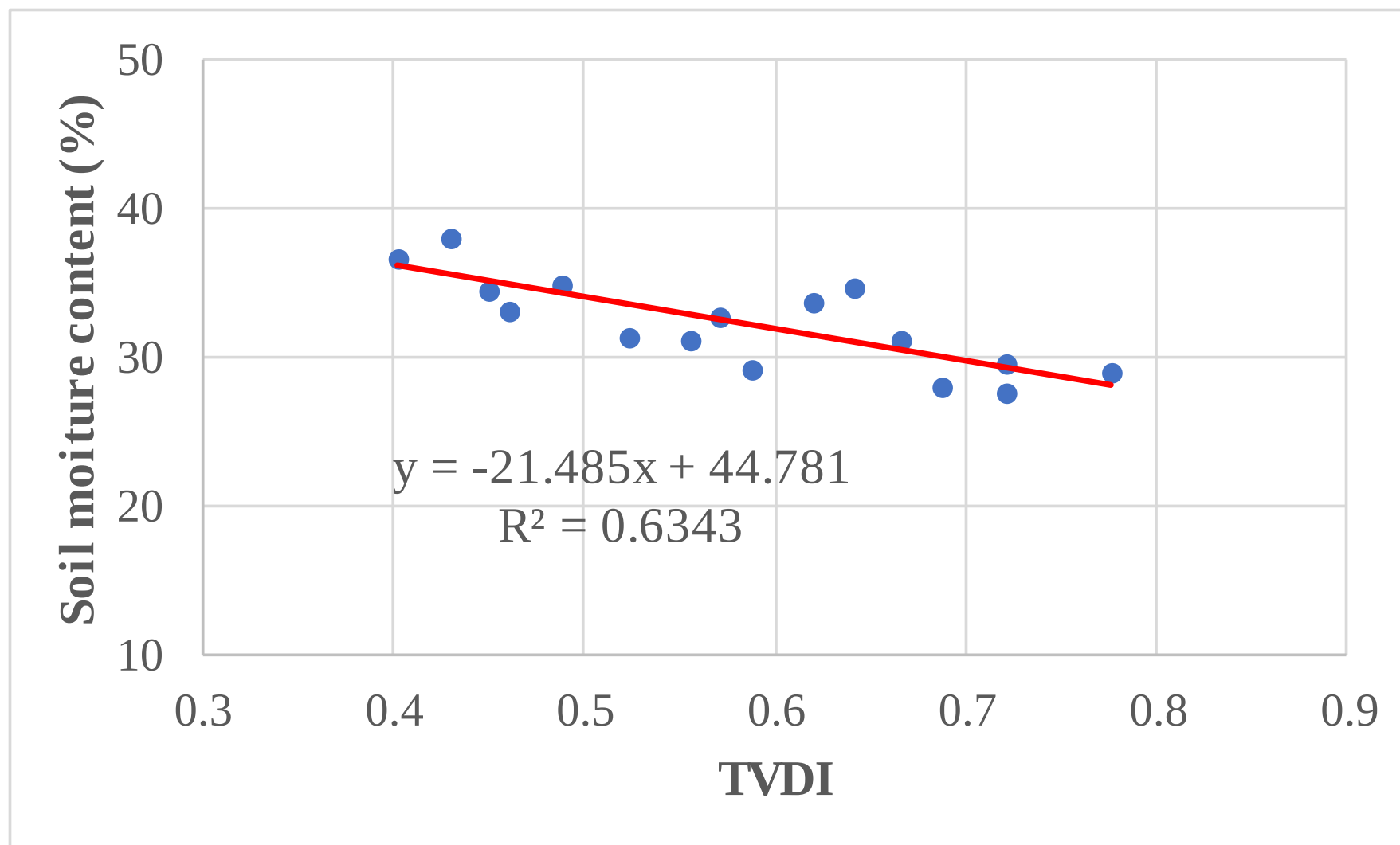
Spatial distribution of soil moisture



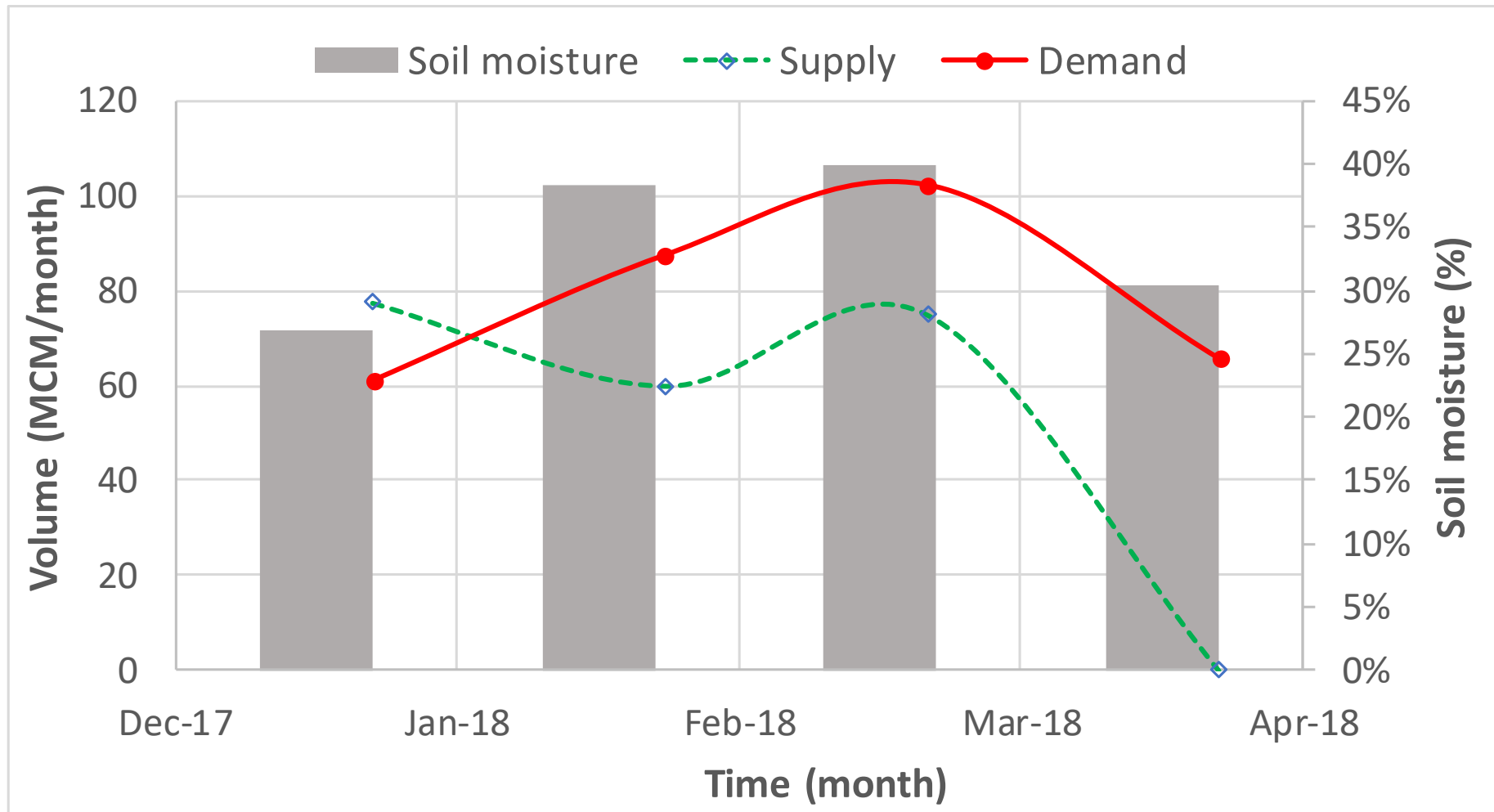
Cultivated paddy area based on NDVI classification

Zone	Cultivated ratio (%)								Estimated cultivation area (RAI)	Report cultivation plan (RAI)
	19-Jan	4-Feb	20-Feb	8-Mar	24-Mar	9-Apr	25-Apr	Average		
1	36%	47%	48%	51%	52%	49%	36%	46%	134,219	
2	45%	36%	31%	43%	47%	49%	45%	42%	98,225	
3	48%	45%	44%	49%	50%	53%	46%	48%	135,871	
Total									368,315	380,557

Correlation between TVDI coefficient and observed soil moisture content from GISTDA

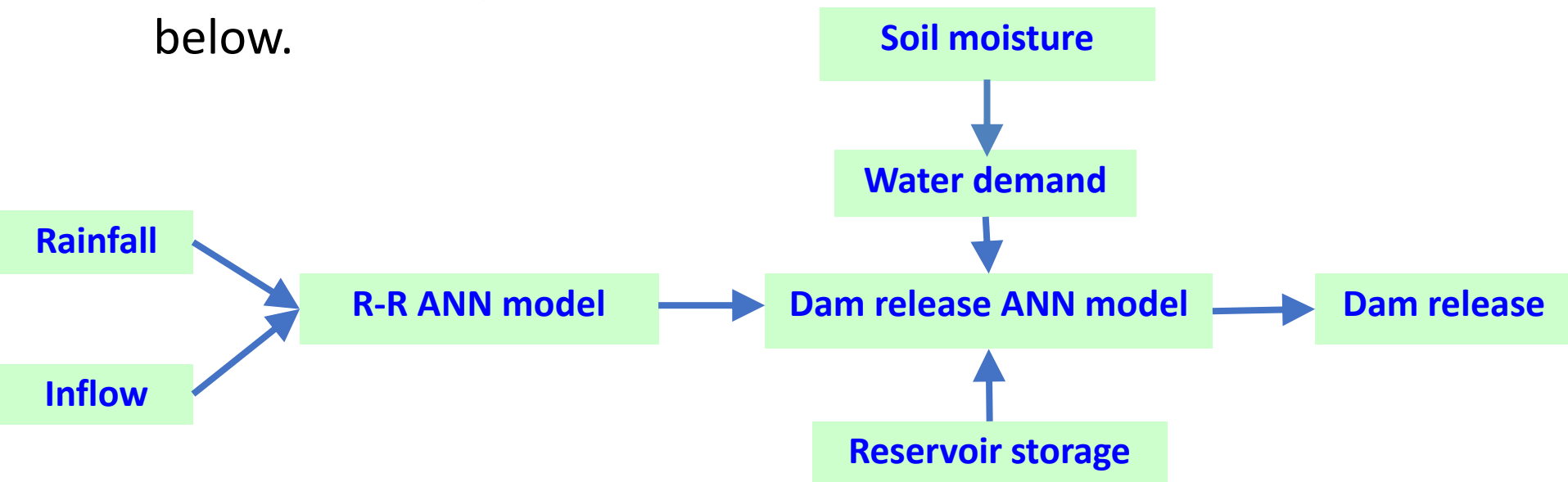


Monthly amount of irrigation water demand/supply and soil moisture



Future works

- Previously, the dam operation is set by demand estimate from the past average record and controlled by upper and lower rule curve. With the developed rainfall-inflow-release data from ANN and soil moisture based irrigation demand, **the dam release can be re-optimized with the more real time information to get up-to-dated inflow and demand** as shown below.



Conclusions

- ANN technique can capture the **inflow** from rainfall data and **dam release** from dam storage while satellite images with ground **soil moisture sensor data** helped to estimate **irrigation demand** in near real time and accurate enough for development of smart dam operation system.
- The results show how **smart system concept** was applied and improve dam operation by using inflow estimation from ANN technique combining with irrigation demand estimation from satellite images when compared with the past procedure
- Next step is to develop the smart decision making for **dam release**.

Acknowledgement

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