

Impacts of Future Climate Change in Water Resources Management at the Chao Phraya River Basin, Thailand

2020

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A Dissertation submitted in partial fulfillment of
the requirements for the degree of
Doctor of Engineering

Department of Environmental Engineering
Graduate School of Engineering

Kyoto University
Kyoto, Japan
2020

ABSTRACT

In the heart of Thailand, food and water resources always allude to the Chao Phraya River Basin (CPRB) due to the characteristics of the basin: 43% of the area being floodplain and annual rainfalls of above 1,200 mm. However, those strengths can sometimes turn into risks due to the impacts of climate change. The frequency of floods and droughts in the basin has risen year after year starting in 2005. In 2011, the massive floods hit the basin for over three months, with devastating impacts in terms of human lives, agricultural damages, and economic losses. Also, droughts affected up to 10% of the agricultural area from 2009 to 2015. In reference to climate change, the Thai government has envisioned that water resources management could mitigate coming floods and droughts. The Master Plan focusing on water resources management has provided new regulations of reservoir operations and proposed detention ponds for flood protections. To reduce the impact of drought events, the Free Pond Construction Project for non-irrigated areas were provided by the Land Development Department (LDD). However, those plans do not consider how the changes in water resources management and future climate will influence the flow regime. This key question is processed in the four objectives in this dissertation: (1) to construct hydrological model, climate change approaches, a pond management model, and reservoir operations model for the CPRB, (2) to predict trends of future rainfall and the temperature relevant to climate change, (3) to provide information on climate-adaptive pond management, and (4) to investigate the impacts of future climate change, reservoir operations, pond management, and the combination of those factors on the flow regime.

Chapter 2 provides knowledge and peer-review information from existing literature as well as opens a discussion for research methodology. Given the first objective, pros and cons in order to select a hydrological model, climate change approaches, a pond management model, and a reservoir operation model have been reviewed. Furthermore, water resources management strategies were introduced, particularly the pond management and reservoir operations done by modelling. The Hydrological Simulation Program-Fortran (HSPF) model was selected to use for the CPRB due to flexible parameter adjustments and special command setups relevant to a natural phenomenon and manmade operations. For the climate change data, since Policy Decision Making for Future Climate Change (d4PDF) includes 4-degree Celsius increase of future climate simulation and advantages of many previous models, it was the best choice to predict future extreme events.

Chapter 3 has applied the HSPF model based on the characteristics of the CPRB. Through calibration and validation, the Nash-Sutcliffe efficiency (NSE) values between 0.51 and 0.83 have confirmed a satisfactory and good performance, which can be used to simulate daily river discharges at 12 gauge-stations. Pressure on dam operations has gradually emerged following the great flood of Chao Phraya River Basin in 2011. Looking for applicable management for flood prevention, this chapter also evaluated the effectiveness in preventing floods by two possible adjustments (*i.e.*, daily release storage ratios and the timing of water release) for two large-scale dams. The author also dealt with the scenarios of detention ponds, including the proposed retarding basins by the Thai Master Plan and the suggested new detention pond. The model performance expressed a very good performance rating under flood conditions. The results have highlighted that the appropriate daily release storage ratios during dam operation were in the range of

0.007-0.008 during the July-August period and 0.001-0.002 during the September-October period. The retarding basins, however, were not so effective in damping floods in general. A better solution offered the integrated watershed management by combining both advisable scenarios of dam operations and detention ponds and consequently achieving 94 percent of overflow volume reduction.

Chapter 4 was aimed to build up approaches for the post-processing of d4PDF data based on CPRB conditions. Interpolation and bias corrections were key methods in the post-processing. By the interpolation using the Gradient-plus-inverse-distance-squared (GIDS) method, the available observed climate data at 22 meteorological stations were successfully interpolated into 57 gridded cells. In general, the d4PDF data were corrected through observed climate patterns using appropriate bias correction approaches. Because of the different patterns between rainfall and temperature, the bias correction methods used for precipitation could not be applied to the temperature. With regards to the rainfall pattern, time windows, seasonality, and month were adjusted in the bias correction methods. In order to predict extreme rainfall, the gamma distribution combined with a Generalized Pareto Distribution (Gamma & GPD) approach with a seasonal time window setup was applied to the rainy season datasets. The dry seasonal datasets were corrected by the gamma distribution approach while setting the monthly time window to increase the number of days with no rainfall. The developed bias correction methods for rainfall could achieve to react to extreme rainfall events, to expand dry days during the dry season, and to intensify the rainfall amount during the rainy season. Moreover, the Equidistant Cumulative Distribution Function Matching (EDCDFm) was used to correct the maximum and minimum temperatures. The d4PDF temperature patterns were successfully corrected in a similar trend with observation. This chapter also included

trends of post-processing the d4PDF outputs with three ensembles (MI, MP and MR) including 45 ensemble members of two periods (2051-2070 and 2091-2110). A similar trend of annual rainfall was indicated through the MI and MP ensembles. A significant difference was the reduction of the annual rainfall by the MR ensemble of about 500-1,000 mm shown downstream of the Ping River Basin, the Upper CPRB. For the extreme rainfall, a maximum annual rainfall above 3,000 mm/year was projected by three ensembles.

Since so far the specific pond capacity for the Free Pond Construction Project for non-irrigated areas was planned and started without considering the characteristics of the CPRB, local conditions, water requirement, and protection of flood events and droughts, Chapter 5 was aimed to achieve the third research objective. The aim was to construct a pond management model including factors of water demand, water balance in ponds, and benefits in view of increasing agriculture yields. Those factors were driven by three models, the water requirements model, the water budget model and the economic model. Three classified types of ponds (public, private and future ponds) were simulated by different pond operation rules based on the monthly water demand, and the protection against floods and droughts. Also, three ensembles of the future climate data from Chapter 4 were used to predict the daily pond inflow, the daily pond release, and the water level to estimate pond capacities. At greater than 80% of pond reliability, the results showed that public ponds should have a pond ratio of 1-4 m of capacity/area in floodplain areas. Suitable capacities for private ponds were in the ranges of 500-3,250 m³ for minimum capacity and 1,800-3,250 m³ of maximum capacity. The minimum capacity of future ponds was suggested to be in the range of 1,000-3,000 m³ with a depth range of 2-4 m. The maximum pond capacity should be over 5,000 m³ with a depth of more than 4 m to

protect future overflows. Due to insufficient water requirements in some areas, it was suggested to construct about 1,000 units of future ponds in each sub-district. In the economic model, the results have shown that constructing a lower number of ponds at maximum capacity could earn more benefits.

In Chapter 6, an optimization modelling for reservoir operation was constructed, since the reservoir operation of the two large-scale reservoirs played a significant role in the flow regime in the CPRB. The Adaptive Neuro-Fuzzy Inference System (ANFIS) was applied by setting four basic inputs (reservoir inflow, storage, rainfall and water demands) with adjustments of the membership functions (MFs) and additional setups indicating seasonality and month. Eight different forms of MFs were examined. The trapezoidal-shaped membership function was chosen due to the good initial performance. The basic parameters with the additional input indicating the month could obtain better performance for Bhumibol Dam's model. For Sirikit Dam's model, the model performance by adding the monthly input showed a minimal improvement when compared with the seasonal setup. The optimized performances, NSE values, to simulate daily reservoir discharges for Bhumibol and Sirikit Dams were 0.43 and 0.47, respectively. In order to achieve an effective reservoir operation for protection against floods, the additional reservoir operation has been suggested for the timing and the daily release storage ratios (r). The simulated water release by adding the daily release storage ratio (r) of 0.006 is recommended to use at the mid-rainy season (July-August), and the ratio (r) of 0.001 should be applied at the end of the rainy season (September-October). These ratios were examined by their impacts on river flow, and the results show that the flood peaks could be decreased. In consideration of drought mitigation, the operation was designed to increase the daily water release of 14 million cubic meters (MCM) for Bhumibol Dam

and 7 MCM for Sirikit Dam when the Lower CPRB has no rainfall for over seven days. This chapter also included the future d4PDF climate data of three ensembles. The future reservoir discharges at the mid of the rainy seasons were about 500-2,000 MCM per month and less than 400 MCM per month at the end of it. During the rainy seasons, about 6,000-8,000 MCM would be stored at both dams to support water for the next dry season. The dams tended to discharge about 700-1,200 MCM per month during the dry season.

Chapter 7 investigates the impacts of the future climate change, reservoir operations, and the pond management on the flow regime. The results of post-processing d4PDF in Chapter 4, the daily pond water release in Chapter 5, and the daily reservoir discharge in Chapter 6 were input in the hydrological model constructed in Chapter 3. The future daily river discharges were predicted through three ensembles (MI, MP and MR) for two periods (2051-2070 and 2091-2110) at five gauges-stations in the Upper and Lower CPRB. The annual maximum daily flow relevant to non-exceedance probability was analyzed flood frequency. The result indicated that the flood frequency during the period 2091-2110 was greater than during the period 2051-2070. Because of impacts from climate change and reservoir discharge, the extreme daily flow could be in the range of 5,500-6,800 m³/s at the CPR origin. Related to the annual rainfall reduction in the downstream of Ping River predicted in Chapter 4, the period up to 80 days might have no flow as well as a water shortage at mid-stream of CPR. One of the most benefits within future impacts of pond management was the reduction of extreme peak flows at the end of rainy seasons (August-October). Also, the mitigation of water shortage was projected during the low flow.

The final chapter summarizes the important research findings as mentioned above. Since the model performances of reservoir operations were unsatisfactory for Bhumibol

and Sirikit Dams in Chapter 6, issues and suggestions were provided in order to improve the model performance in further researches. In Chapter 7, through pond management, the timing change and the quantity increase of the annual maximum daily flow at the Upper CPRB were the undesirable impacts. The timing of pond water release at the beginning of the rainy season (May-July) should be considered more because the pond should release water based on the characteristic of the flow regime in each sub-basin. Due to the insufficient river capacities in the CPRB, future Thai government plans should include the increase of the river capacities about 2,400-2,800 m³/s for the Upper CPRB and 3,900-5,200 m³/s for the Lower CPRB based on the results of annual maximum daily flow obtained in Chapter 7.

ACKNOWLEDGEMENT

I would first like to express my greatest gratitude to my professor, Prof. Yoshihisa SHIMIZU, for his suggestions, guidance, and supports. He suggested not only the immense knowledge and ideas but also the other aspects during the five years of my Master and Doctoral courses in the laboratory of Water Quality Management, Department of Environmental Engineering, Kyoto University. Also, I appreciate his understanding of when I had any problems. Without his kindness and support, I could not have completed my PhD course.

I would also like to thank Prof. Hiroaki TANAKA and Prof. Minoru YONEDA for acting as my committee members, giving significant recommendations and letting my dissertation defense to be an unforgettable experience.

I would also like to thank my laboratory members. I'm very thankful to Dr. Ho Huu Lo, Khagendra Bharambe, and Jacky Wong for their suggestions, ideas, and knowledge. They also gave comments to improve my research. The special thanks are for Dr. Shang Shen, Ryosuke Homma, Dr. Taishi Yazawa, Dr. Daigo Shimizu, Rei Nakayama, Kamiya Akinori, Yoshimi Nishio, and other lab-mates who supported and helped in any way.

I would like to thank my mother, Mr David Stenzel, Dr. Patinya Hanittinan, Dr. Randolph Ruiz Rodriguez, Mr. Teerawat RAM-INDRA, Asst. Prof. Teeranee Techasrivichien, Mr. Thatkiat Meema, Dr. Donpapab Manee, and other friends who were always willing to help and give the best encouragement.

Since I have done experiments at the Environmental and Water Resources Engineering Laboratory, Department of Civil and Environmental Engineering and at the Laboratory of Department of Chemical Engineering, Mahidol University, Thailand, I would like to express my gratitude to Assoc. Prof. Dr. Suwanna Kitpati Boontanon, Asst. Prof. Dr. Wanida Koo-amornpattana, and Dr. Sira Srinives for advising, supporting equipment and providing some chemicals. I also would like to thank their students and officers, who are Ms. Pitchaya Piyaviriyakul, Ms. Saratsawadee Sukeesan, Ms. Thaneeya Samwang, and Mr. Chonlathon Kinkaew for help during my time at Mahidol University.

My special thanks and gratitude are communicated to Royal Irrigation Department of Thailand (RID), Hydro and Agro Informatics Institute (HAII), Land Development Department, Thai Meteorological Department (TMD), Electricity Generating Authority of Thailand (EGAT), Pollution Control Department (PCD), and others departments for their cooperation and support. I also appreciate Ms. Kanjanawan Nilklud, an officer of RID and Mr. Theerapol Charoensuk, an officer of HAII for their suggestions, cooperation and data preparation.

Finally, I also gratefully acknowledge the Japanese Government (Monbukagakusho: MEXT) associated with Human Security Engineering (HSE) program for granting the scholarship during studying in Japan.

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LIST OF ABBREVIATIONS

APHRODITE	Asian Precipitation–Highly Resolved Observational Data Integration Towards Evaluation of Water Resources
ADB	Asian Development Bank
AGCM	Global atmospheric general circulation
ANFIS	Adaptive network-based fuzzy inference system
ANN	Artificial neural networks
CDF	Cumulative Distribution Function
CDFm	Cumulative Distribution Function-transform matching
CDF-t	Cumulative Distribution Function-transform
CGD	Comptroller General’s Department
CMIP	Coupled Model Intercomparison Project
CPRB	Chao Phraya River Basin
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DEM	Digital Elevation Model
DIAS	Data Integration and Analysis System Program
DMIP	Distributed Model Intercomparison Project
DWR	Department of Water Resources
d4PDF	Policy Decision Making for Future Climate Change
EGAT	Electricity Generating Authority of Thailand
EDCDFm	Equidistant Cumulative Distribution Function matching
FAO	Food and Agriculture Organization of the United Nations
FIS	Fuzzy Inference Systems
Gamma	Gamma distribution
GCMs	General circulation models
GDP	Gross domestic product
GIDS	Gradient-plus-inverse-distance-squared
GISTDA	Geo-Informatics and Space Technology Development Agency
GPD	Generalized Pareto Distribution
HSPF	Hydrological Simulation Program-Fortran
HAIL	Hydro and Agro Informatics Institute
IDW	Inverse Distance Weighted Interpolation

IPCC	Intergovernmental Panel on Climate Change
JICA	Japan International Cooperation Agency
JMA	Japan Meteorological Agency
LDD	Land Development Department
LRC	Lower Rule Curve
MAE	Mean Absolute Error
MCM	Million cubic meters
MFs	Membership functions
MRI	Meteorological Research Institute
NHWL	Normal High-water Level
NN	Nearest Neighborhood
NSE	Nash-Sutcliffe efficiency
OAE	Office of Agricultural Economics
OECD	Organisation for Economic Co-operation and Development Office
PET	Potential evapotranspiration
PIM	Pond-Irrigation Model
QM	Quantile mapping approach
R	Correlation coefficient
RCM	Regional climate models
RID	Royal Irrigation Department
RMSE	Root Mean Square Error
RSR	RMSE-observation standard deviation ratio
SCWRM	Strategic Committee for Water Resource Management
SIC	Sea ice concentration
SST	Sea surface temperature
STELLA	Structural Thinking, Experimental Learning Laboratory with Animation
SWAT	Soil and Water Assessment Tool
TMD	Thai Meteorological Department
TRMM	Tropical Rainfall Measuring Mission
URC	Upper Rule Curve
USDA	United States Department of Agriculture
USEPA	US Environmental Protection Agency
USSCS	US Soil Conservation Service

Chapter 1

Introduction

1.1 Research Background

The Chao Phraya River Basin (CPRB) in Thailand is the most significant area for rice and agricultural plantations due to 43% of the area being a floodplain, an average annual rainfall of above 1,200 mm, and suitable soil property. However, those strengths sometimes return to weaknesses when heavy and extreme rainfalls occur. Because of the muddy and flat ground, water cannot drain as fast as people want when it seems that the rain won't stop. At the same time, the sea-level altitude of the delta causes a fast increase of the water level in the river. Another problem is that the people cannot hear the sound of water movement at all while the water is overflowing, so there is no early warning possible. What can Thai people do when they see this situation? We need to move our important property to the second floor and try to prevent the flooding of our homes by sandbags. However, not everyone has a second-floor house. What they can do instead is to wish that the water level decrease as soon as possible.

1.1.1 Problem Statement

However, luck does not always happen. Thai people have experienced more frequent inundations and floods, particularly starting from 2005 as shown in Figure 1.1. Inundations during rainy season occur downstream of the Yom and Nan River Basins and along the Chao Phraya River year after year. The floods of 2006 and 2010 are of medium-

scale in consideration of loss. Floods have been reported to be the origin of massive losses of agricultural productions and property almost every year (Garbero and Muttarak, 2013).

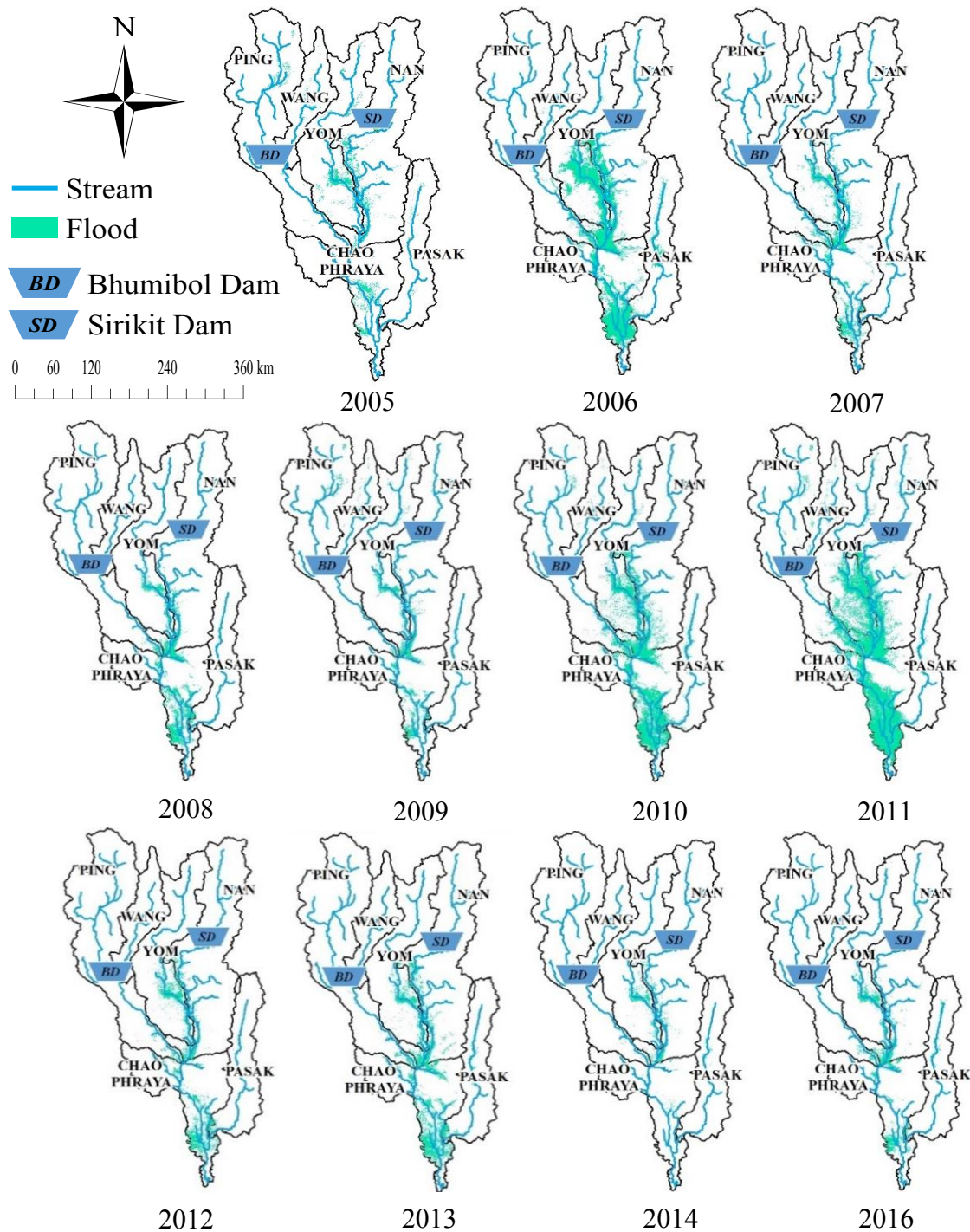


Figure 1.1 Flood areas of the years 2005-2016 (Data has been provided by Geo-Informatics and Space Technology Development Agency (GISTDA), Thailand)

Especially in 2011, the most extreme flood in the history of Thailand took place for over five months from August to December. Devastating losses of agricultural area, people and economy have been reported by the World Bank, 2012. About US\$ 1,318 million of damage in the agriculture sector and US\$ 45.5 billion of total economic losses were estimated (Poapongsakorn and Meethom, 2012). Also, 813 casualties with three additional people missing were counted, and over 66 provinces were affected by the flood in 2011.

Not only floods but also droughts hit the basin in 2005, 2010, 2012, 2014, 2015, and 2016. Droughts mostly affect the water utility and agriculture sections in term of production yields. During the dry season, water scarcities of CPRB in the years 2009, 2010, 2012, 2014 and 2015 were 1,331 million m³, 2,339 million m³, 1,531 million m³, 1,965 million m³, and 1,213 million m³, respectively (HAIL, 2015). These volumes were measured by the deficient water volume in reservoirs and water demands. The impacts of the droughts can be expressed in term of economic disruption, particularly in a share of the agriculture in the gross domestic product (GDP) as in Figure 1.2. The droughts affect about 2.5 to 10.0% of the agricultural area from 2009 to 2015. In some years, both drought and flood occurred so that the share of agricultural land affected was over 50%. In the meantime, even when the annual rainfall exceeded the average, CPRB has experienced droughts due to climate variables that contribute to precipitation, temperature, evaporation, evapotranspiration, and wind direction (OECD, 2018).

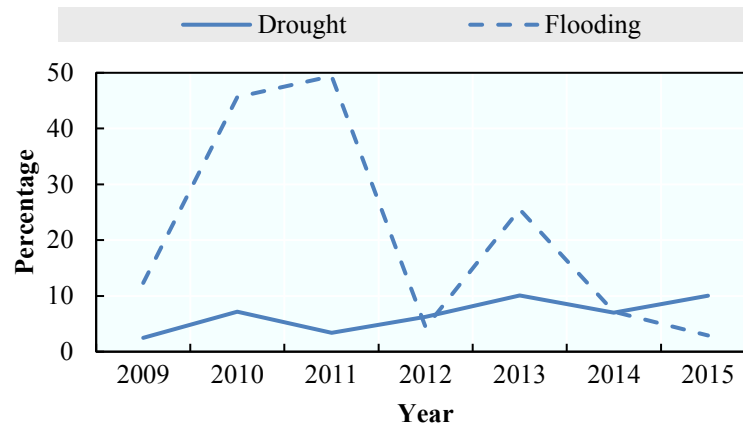


Figure 1.2 Agricultural land affected by drought or flood (Information provided by OECD, 2018)

1.1.2 Motivation

An increase of floods and droughts has been seen in the last two decades due to climate change affecting the rainfall patterns in CPRB after 1980 (Promchote *et al.*, 2016). As experiences from previous floods and droughts show, climate change is mostly a problem because the relevant trends of pre-monsoon, extreme rainfall, and rainfall intensity are not explored enough (Kure and Tebakari, 2012). Pre-monsoon caused by the northeast winds from East Asia. Their rainfall duration and frequency have significant impacts on the hydrological processes, basin characteristics, and flow regime. Accordingly, several questions have been discussing the effects of climate change; for examples

How extreme and heavy the rainfall will be in terms of amount and
duration during the rainy season?

What is the most drawn-out duration of no rainfall during the dry season?

With what frequency will extreme floods occur in the future?

In order to obtain the solutions of them, climate change models involving extreme rainfall events should be researched for CPRB. The aim is not only to answer those questions and to understand the changes but also to consider and plan how to prevent and mitigate both flood and drought events in the future.

Impacts of climate change are mostly on hydrological processes. Changes in the processes affect simultaneously all water management, *e.g.*, water resources, water uses, water supply, *etc.* Effective water management plays an essential role to prevent and mitigate future disasters. Being significant flood risk management, after the experiences of the 2011 flood the Royal Irrigation Department (RID) and Department of Water Resources (DWR) collaborated with Japan International Cooperation Agency (JICA), and proposed new regulations for large scale reservoirs. Retarding basins and retention areas in the CPRB were also advised to do flood prevention, as suggested in the Master Plan on Water Resource Management Report (SCWRM *et al.*, 2012). Several projects proposed by the plan, however, have not been constructed in the Upper CPRB region because of the lacking cooperation strategy between the water resource management and budgets of the Thai government (ADB, 2013; Jamrussri and Toda, 2017).

In order to perform drought mitigation, the Land Development Department (LDD) provide the Free Pond Construction Project for non-irrigated areas. The LDD supports the construction of ponds with a capacity of 1,260 cubic meters for farmers. The LDD has constructed ponds of 68,177 units in CPRB from 2005 to 2018. Over 58,000 ponds are required to be built in the future. However, this specific pond capacity might have negative impacts on the flow regime without considerations of area characteristics, rainfall pattern and local conditions.

Even though the Thai government has been developing several projects including structural and non-structural measurements in CPRB after the massive 2011 floods, water resource management is still ineffective due to the lacks of information, research, and the corresponding budgets. In this dissertation, three major scopes are taken into account, climate change, hydrological processes and integrated watershed management. Due to the above-mentioned significant impacts of climate change, an increase of 4-degree Celsius is applied in the hydrological model; and, two strategies for water resources management that are pond management and reservoir operations are presented. Pond management is motivated by the LDD's project since the incorrect construction and management of current ponds, and a large number of future ponds might be a severe issue for flood risk. Also, reservoir operations of large-scale dams are studied in relation to the climate change in order to improve the operations for water usage optimization and floods and droughts reduction. The increase of pond numbers and changes in reservoir operations might be affecting the characteristics of runoff and river flow. Consequently, the focus lies on the effects of the changes in climate and the strategies for water resources management on the flow regime.

1.2 Research Area

The Chao Phraya River Basin (CPRB) covers an area of 156,618 km², accounting for 31% of Thailand's area. Their geographical coordinates are from 98° 3' 53.92" to 101° 31' 20.51" East longitude and from 13° 32' 22.44" to 19° 48' 38.12" Northern latitude (Figure 1.3). The CPRB includes the Ping, Wang, Yom, and Nan tributaries. These rivers originate from the mountainous area in the north and merge into the CPR at Nakhon Sawan Province. The Tha Chin River splits off the mainstream at about 80 km

downstream of the CPR origin. Within the scope of this dissertation, the drainage area of Tha Chin River Basin is not included since the river is a distributary of the Chao Phraya River and drains directly into the Gulf of Thailand. The Pasak River converges into the Chao Phraya River 99 km upstream of Chao Phraya delta.

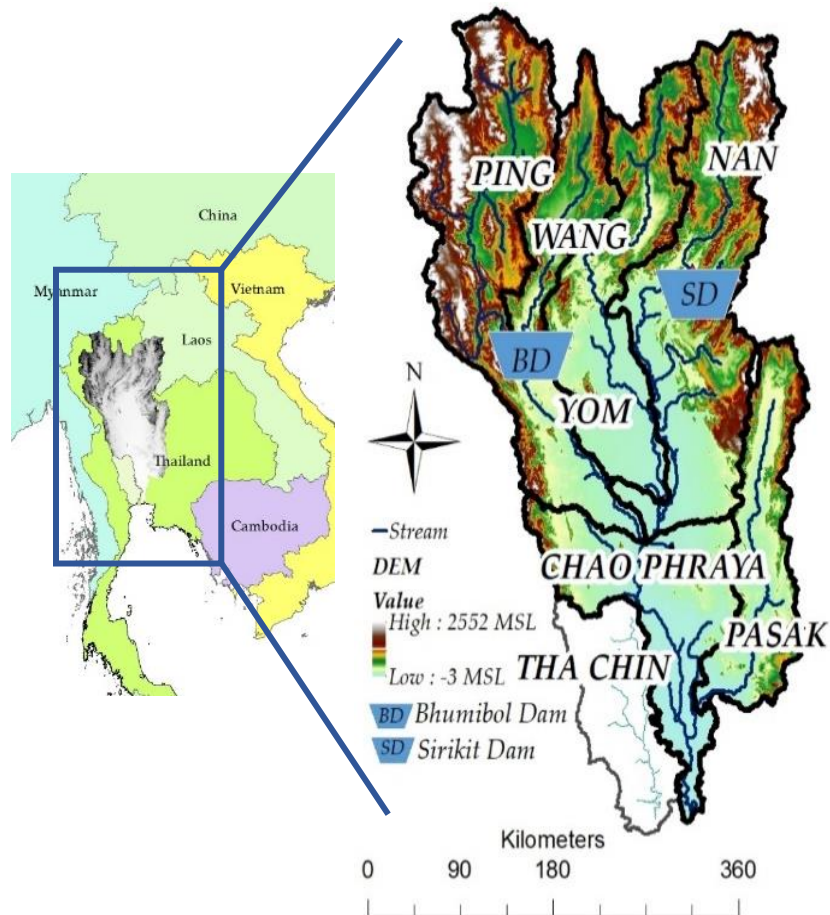


Figure 1.3 Map of Thailand and Chao Phraya River Basin

In the CPRB the rainy season lies between mid-May and mid-October, bringing a huge amount of rainfall from the Indian Ocean under the effects of the Southwest Monsoon. The dry season lasts from mid-October to mid-May, affected by the Northeast Monsoon with dry air and low temperature (Aon, 2012).

The landscape of the northern region consists of mountainous areas and steep slopes. According to the area characteristics, agricultural area and forest cover about 13 to 40% and 14 to 42% of the Upper CPRB's area, respectively. However, the Lower CPRB is mainly covered by paddy fields, which covers 23 to 40% of the total area, because of the floodplain characteristics and the local weather.

Due to the large agricultural areas, an irrigation project on downstream of Bhumibol Dam, three projects on downstream of Ping River supporting water to areas of Yom River Basin, and four projects on downstream of both Nan and Yom Rivers are carried out as shown in Figure 1.4. Additionally, over 30 irrigation projects have initiated the operation in the Lower CPRB. These irrigation projects are meant to support water for agricultural areas in the basin. Moreover, other irrigations, including large and small scales of water resources, play an essential role for the water supply in order to increase the agriculture production yield.

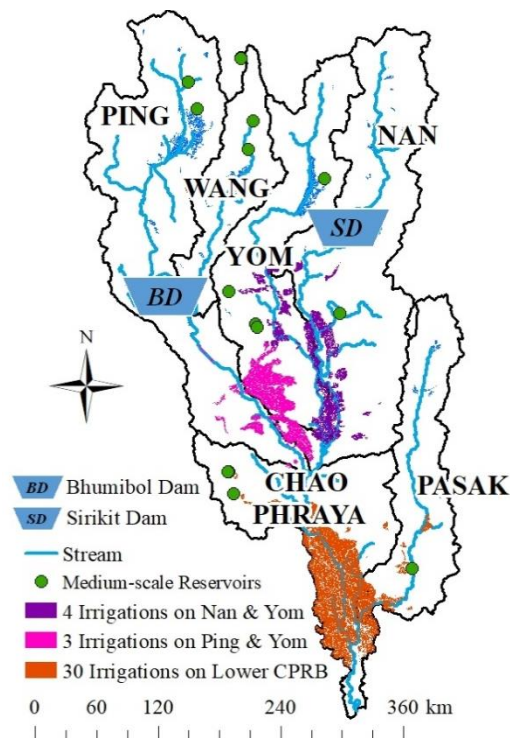


Figure 1.4 Locations of Reservoirs and Irrigation Projects

1.2.1 Reservoir Operations

The water resources management in the basin is operated by the Royal Irrigation Department (RID), the Electricity Generating Authority of Thailand (EGAT), and local governments. The irrigation systems of the basin are shown in Figure 1.4. Dam operation is a vital irrigation technique by controlling the river discharge. The thirteen medium-scale dams, green dots in Figure 1.4, are operated by RID or/and EGAT in the Ping River, Wang River, Nan River, and Chao Phraya River. For the large scale of reservoirs, Bhumibol Dam and Sirikit Dam are being operated by RID and EGAT together. The origin of the Chao Phraya River is located approximately 240 km downstream from Bhumibol Dam and 360 km downstream from Sirikit Dam in Figure 1.4. The numerous significant purposes of the two dams include flood and drought mitigations, water supply for downstream, hydro-electrical energy generation, salt intrusion control, and maintenance of the environmental flow during the dry season. The general description of the dams is shown in Table 1.1.

Table 1.1 General Description of Bhumibol and Sirikit Dams (from Electricity Generating Authority of Thailand (EGAT) and Royal Irrigation Department (RID))

Description	Unit	Bhumibol Dam	Sirikit Dam
Latitude	-	17° 14' 31" N	17° 46' 05" N
Longitude	-	98° 58' 31" E	100° 33' 15" E
Drainage Area	km ²	26,386	13,130
Storage at Maximum High-water Level	million cubic meters (MCM)	13,462	10,508
Maximum High-water Level	m	260	166
Normal High-water Level	m	260	162
Minimum Water Level	m	213	128
Average Annual Inflow	million cubic meters (MCM)	5,704 (1965-2010)	5,638 (1974-2010)
Date of Completion of Construction Works	-	June 1964	July 1974

In general, the dam operation is to serve and store water during the rainy season, especially from August to October. Then, the dams release the water for agricultural demands during the dry season. However, the dams have some criteria to control the water volume between Upper Rule Curve (URC) and Lower Rule Curve (LRC). And, these criteria are a non-structural measure for flood mitigation. The criteria for dam operation are corresponding with the water level in the dams as follows (Vongphet, 2015):

- Discharge excess water when the water level is higher than a Normal High-water Level (NHWL),
- Discharge water to supply the water demand when the water level is higher than URC,
- Discharge more water to reserve space of storage in flood case when the water level is higher than URC and has a tendency of the flood situation,
- Release water according to the water demand when the water volume is between URC and LRC,
- When the water level is lower than LRC, the water release is prioritized as a paramount concern, and
- Stop water discharge when the water level reaches a minimum water level.

In general, the rule curves are adjusted to balance the demand for agriculture, consumption, ecological conservation, and flood protection. In CPRB, the dam operation plays an essential role for flood control. Previous rule curve rules are inappropriate because it is the one factor that caused the devastating impacts of the floods in 2011. Accordingly, in 2012 new rule curves for both Bhumibol and Sirikit Dams have been designed to accommodate a larger water storage volume during the rainy season. Notably, the new URC has been adjusted to a lower value than old rule curves at the middle of the

rainy season. Given the purposes of flood protection and mitigation, dam operations are consequently a key approach of water resources management.

1.2.2 Construction and Management of Ponds

Small scale reservoirs, including ponds, are an alternative water resource in general. Significantly in CPRB, ponds are given a key position for the purpose of agriculture irrigation during the dry season. In non-irrigated areas, numerous ponds are located to maintain water during the rainy and dry season. The existing ponds are classified into public and private sectors as in Table 1.2. Public ponds are mainly operated by the Royal Irrigation Department (RID), Land Development Department (LDD), and local administrations. Owners and farmers generally operate private ponds. More specially, LDD has been supportive to construct public and private ponds under two running projects: Project of Soil and Water Conservation and Free Pond Construction Project for non-irrigated areas since 1981 and 2005, respectively.

Table 1.2 Numbers of existing ponds in differences of purposes and operators (Data provided by LDD and Department of Water Resources and its recorded until 2018)

Basin	Agriculture purpose				Multi-purposes			
	Private on-farm ponds		Public Ponds operated		Public Ponds operated		Public Ponds operated	
	supported by LDD		by LDD		by others		by others	
	Numbers of Ponds	Capacity (MCM)	Numbers of Ponds	Capacity (MCM)	Numbers of Ponds	Capacity (MCM)	Numbers of Ponds	Capacity (MCM)
CHAO	3,600	4.54	262	16.78	2,082	406.91	1,006	709.49
PHRAYA								
NAN	18,343	23.11	377	22.38	859	207.11	597	114.67
PING	29,747	37.48	1,065	32.40	612	45.81	1,338	331.86
YOM	11,597	14.61	432	18.39	462	102.58	250	4,510.30
WANG	4,890	6.16	131	10.35	36	20.66	36	47.09
PASAK	No Data	No Data	34	2.44	634	71.85	202	41.38
Total	68,177	85.90	2,301	102.74	4,685	854.92	3,429	5,754.80

The number of existing ponds for agricultural irrigation purposes are 68,177 units (86 million cubic meters) and 6,986 units (958 million cubic meters) operated by private and public sectors, respectively. Regarding other usages of ponds, 3,429 public ponds with their total capacity of 5,755 million cubic meters of water exist in the basin. These numbers are an underestimation compared with the actual numbers. This is caused by a lack of records and recorded ponds in the scope of governmental projects.

The ponds for agricultural objectives generally have a small-capacity, and they are located on the local farms in order to reduce costs of the irrigation system and energy for water transportation. Accordingly, the LDD has started the project of free pond construction for non-irrigated areas with the purpose to support farmers, to increase the agricultural yield, and to raise the average farmer income. On-farm ponds of 68,177 units have been constructed with a capacity of 1,290 cubic meters across CPRB. The specific capacity was studied by/in/on a pilot scale in northeastern Thailand. However, the size is not considering the characteristics of CPRB, local conditions, water requirements, and protections of flood events and droughts (Wangkahart *et al.*, 2008). Moreover, the information on how to operate the pond and how to manage a pond for long-term use is not provided. Accordingly, overflows and water scarcity always occur because of heavy rainfalls and overuses.

1.3 Research Objectives

Due to various climate effects, changes in hydrological processes and strategies of integrated watershed management are set to four specific objectives in this dissertation as follows:

- 1) To construct a hydrological model, a climate change approach, a pond management model, and a reservoir operation model for the Chao Phraya River Basin,
- 2) To understand and predict allocations and trends of future rainfall and the temperature relevant to climate change,
- 3) To provide information on climate-adaptive pond management including appropriate pond design and the numbers of future ponds related to the economic aspect, and
- 4) To investigate the impacts of future climate change, reservoir operations, pond management, and the combination of those factors on flow regime.

1.4 Methodological Framework

For achieving objectives, the methodological framework in this research is shown with the relationship between the chapters in Figure 1.5. Particularly, the problem of CPRB being hit by an increase in the frequency of floods and droughts are summarized in Chapter 1. In the following chapter, the reactions of the Thai government after experiencing climate change impacts have motivated the author to investigate relevant strategies of integrated watershed management. The research area also includes information involving dam operations and pond management.

More knowledge of climate change, hydrological processes and water resources management are gained by the literature review. Chapter 2 discusses the pros and cons of several hydrological models which have been applied by other researches. Considering the future climate change, numerous climate change models and approaches of interpolation and bias corrections are reviewed in terms of advantages and disadvantages.

An overview of water resources management strategies is also highlighted, particularly the pond management and reservoir operations done by modelling.

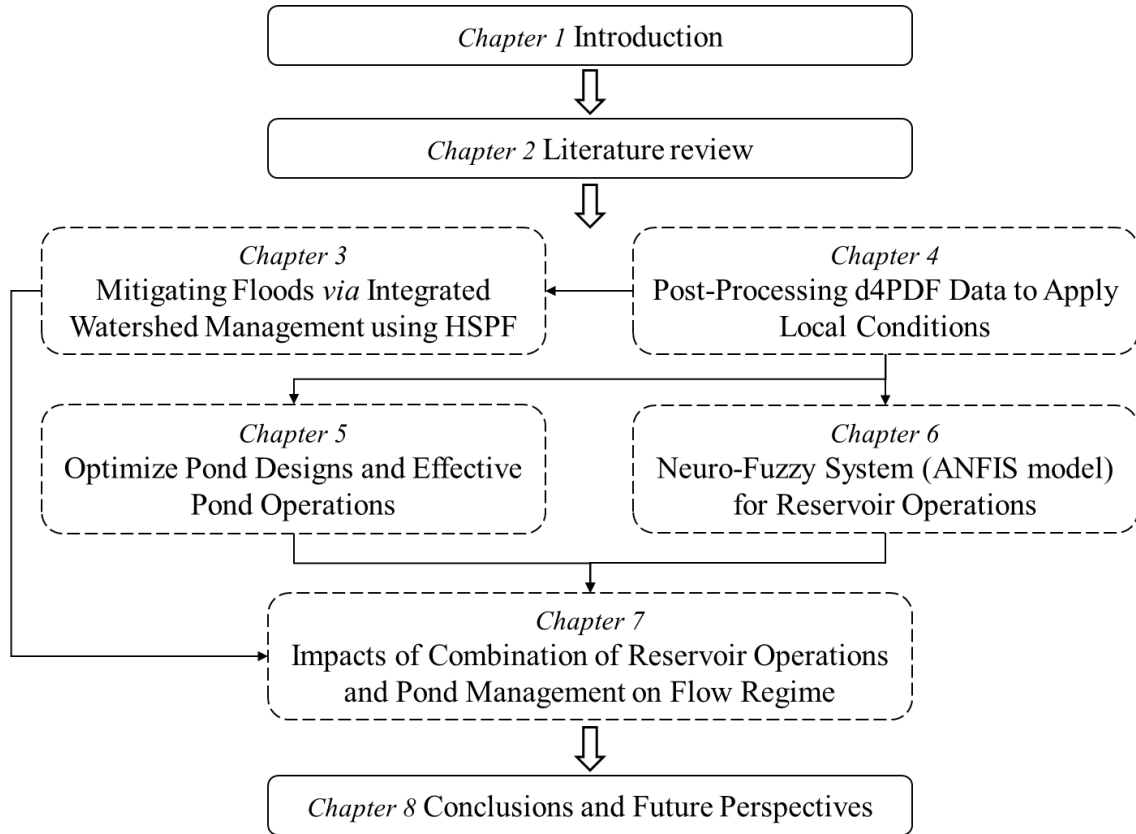


Figure 1.5 Framework of research methodology

In Chapter 3 the development of a hydrological model using a Hydrological Simulation Program-Fortran (HSPF) is shown with in-deep considerations, *e.g.*, characteristics of CPRB, irrigation systems, reservoir operations, detention ponds, hydraulic setup following river capacities, *etc.* In particular, the massive floods of the year 2011 are examined. Two flood management strategies focusing on non-structural and structural measurements are evaluated in the model.

Chapter 4 aims to build up approaches for the post-processing of climate change data based on CPRB conditions. Because of relevant references from the literature review of

climate change models, the d4PDF model is selected to use in CPRB. Accordingly, information and preparation of d4PDF data are explained elaborately. Interpolation and bias correction methods are crucial application for the d4PDF data correction by observation distribution. More specifically, daily rainfall and temperature need different techniques of bias correction due to their unique patterns. Another relevant point of this chapter is the long-term trends and distributions for future rainfall and temperature.

In Chapters 5 and 6, the two water resources management strategies: pond management and reservoir operation, are evaluated by addressing future climate change in developed approaches. Simultaneously, the corrected biases of future climate change data from Chapter 4 are used to simulate climate-adaptive pond management and reservoir operation. Particularly in Chapter 5, the pond management model includes factors of water demand, water balance in ponds, and benefits in view of increasing agriculture yields. Those factors are driven by three models, the water requirements model, the water budget model and the economic model. In order to avoid issues of uncertain hydrological impacts on ponds, the optimal pond design and the effective pond operation in each sub-district are reported. Possible numbers of future ponds are subsequently explored within this chapter taking into account the cost-benefit factor.

Since the reservoir operation of the two large-scale reservoirs plays a significant role in the flow regime in CPRB, an optimization modelling for reservoir operation is required to provide regulations and rules. Within Chapter 6, the Neuro-Fuzzy model (ANFIS model) is applied by setting four basic parameters (reservoir inflow, storage, rainfall and water demands) with adjustments of membership functions and an additional parameter indicating seasonality or month. Model training and validation can consequently identify optimized model performances for the Bhumibol and Sirikit Dams. The relevant climate

change for/with over 40 years of 45 future climatological datasets is simulated in the selected ANFIS models of both dams.

Chapter 7 combines the simulations of the previous chapters from Chapter 3 to Chapter 6. Post-processing d4PDF data (rainfall, maximum temperature and minimum temperature) from Chapter 4 are put into the hydrological model in Chapter 3. Moreover, the results of the pond management model (Chapter 5) and the reservoir operations model (Chapter 6) are also set in the hydrological model. Therefore, impacts of future climate change, pond management, reservoir operation, and its combination are predicted on the flow regime, specifically at significant river discharge stations in CPRB. Finally, Chapter 8 summarizes important research findings and suggests future plans and perspectives.

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Chapter 2

Literature Review

Difficulties of water resource management include decision-making, policy, and implementation, *etc.* Due to the complexity of these natural impacts that are often uncontrollable, it is challenging to make decisions of what to prioritize and what is the most suitable solution for effective management. Decisions in water resource management are vital prior to the planning of large-scale works, investments, *etc.* Accordingly, it is compulsory to perform “Scientification” over time-to-time to understand how the decision impacts various factors, *e.g.*, environment, human, characteristic of area, economy, and social conditions. (Alamanos *et al.*, 2018). As suggested, technologies are preferred due to reliability and promptitude. Since climatology, geography, topography, and hydrology are complicated and asymmetrical, simulation models are the alternative. There have been cases of successful implementation of modeling in water resource management. Climate variabilities critically affect other natural systems, in particular, hydrological processes. Numerous climate change models can assist the examination of the hydrological models (Yang *et al.*, 2010; Tebakari *et al.*, 2012; Fang *et al.*, 2015). Connections of climatological information, hydrological results (river discharges and runoffs), and alternative water resource management strategies (*e.g.*, pond management and reservoir operations) can also be tested and improved by modelling.

In this chapter, section 1 describes the development of hydrological modeling based on the relationships of natural and human-made water resources. Section 2 introduces

climate change and related models, particularly Policy Decision Making for Future Climate Change (d4PDF). The application of climate change models to the local study area is also discussed. Finally, strategies of water resource management are reviewed in section 3.

2.1 Hydrological Modeling

Natural phenomena such as hydrological processes are generally complicated and uncertain; thus, these conditions are difficult to understand from observations only. Numerical modeling is economical, accurate, and can predict the nature variables. Hydrological models comprise of three conceptions that are a physically-based model, an empirical model, and a conceptual model. The physically-based model relates to equations in mathematics and theories. The model has a logical structure that is similar to the realistic systems in the environment. The empirical model compiles the results based on statistical tests, limiting the understanding of the correlation between parameters and output occurrences. The conceptual model integrates the physically-based model and the empirical model. It also considers the physical processes in which input variables drive the output variables (Xu C., 2002). These three models are reclassified into two models in hydrological modeling. First, the lumped model uses the value of each parameter to treat the whole basin. The distributed model uses independent values of each parameter for separated areas and/or sub-basins.

2.1.1 Model Applications

Reed *et al.* (2004) have studied the comparison among 12 distributed models, using the Distributed Model Intercomparison Project (DMIP) and the lumped model. The DMIP

results showed that distributed models significantly improve simulated results through calibration. The accuracy is based on the result of model formulation, parameterizations, and modelers. Also, the determination of parameters following the characteristics of sub-basins in the distributed model is more challenging than identifying reasonable parameters for the lumped model. Meanwhile, the Hydrological Simulation Program-Fortran (HSPF) model, which is a semi-distributed model, has been used to simulate streamflow with a next-generation radar (NEXRAD) in the DMIP. The model has been selected due to the connection between surface dynamics, groundwater, and flexible adjustments in wide ranges of parameter values. Moreover, Ryu *et al.* (2009) have suggested that the HSPF model might be an alternative model to reproduce the hourly flows.

To optimize the simulation, the relationship with land use activities, hydrology, and water quality models should be understood. The US Environmental Protection Agency (US EPA) has developed the Better Assessment Science Integrated Point and Nonpoint Sources (BASINS), which provides Soil and Water Assessment Tool (SWAT) and HSPF. The SWAT model could predict the impacts on hydrology, sediment, and water quality, that is unique to each sub-basin, based on soil and land use type. The runoff is estimated by daily rainfall using the Soil Conservation Service (SCS) curve number method. For the HSPF model, a sub-basin comprises of three modules that are pervious land (PERLND), impervious land (IMPLND), and reaches (RCHRES). These three modules could be adjusted by different values of parameters as a natural phenomenon in the sub-basin. For examples, the infiltration rate could be set using numerous values for agriculture area and forest area in the PERLND module; and the river or reservoir could be set in the RCHRES module. In the differences, Im *et al.* (2003) have simulated flows

using HSPF and SWAT. They reported that the HSPF model gave more accurate results than SWAT. However, HSPF is not user-friendly in a term of parameterization. For daily flow, HSPF has also reported being a better predictor than SWAT (Saleh and Du, 2004).

2.1.2 Hydrological Simulation Program-Fortran (HSPF)

Hayashi *et al.* (2004) have evaluated runoffs of the five main tributaries in the upper region of the Changjiang River Basin in China, which has an area larger than 500,000 km². The HSPF has shown to be a desirable choice for river discharge simulation of large basins. The watershed setup in HSPF consists of three modules to define each segment area with different hydrologic characteristics. The PERLND module simulates water budget (PWATER) based on surface runoff, interception, evapotranspiration, interflow, and infiltration. Groundwater is also considered in the module. The water budget (IWATER) in the IMPLD module is computed by an accumulation of water and evaporation since the infiltration does not occur on impervious land. The RCHRES module could set the characteristics of reach, such as a single channel, open or closed channels, and lake or reservoir in HYDR function (Bicknell *et al.*, 2001). Due to the separated parameter adjustments based on land use, HSPF has well-performance for daily discharge at the Polecat Creek watershed in Virginia (Im *et al.*, 2003). Singh *et al.* (2005) have also performed calibration for monthly and annual streamflow values of the Illinois River Basin. The simulated results of both researches are closely similar to the observed stream flows.

2.2 Climate Modelling and Post-processing Techniques

Hydrological processes are affected by climate change. Several scenarios of future climate change in extreme precipitations have been applied in hydrological models and other models to understand the effects of the extreme floods and to attempt accomplishments of future projects and plans. Thus, future climate change plays an essential role in future water management.

2.2.1 Previous Studies of Future Climate Models

Increasing greenhouse gases, global warming and other factors can affect long-term climate patterns and extreme events. Hence, numerous climate change models are being developed and studied. The general circulation models (GCMs) take into account the complicated conditions, *e.g.*, future changes in greenhouse gases, ocean, *etc.* The well-documented limitation of GCMs is the coarse horizontal resolution that is not appropriate for small studying areas, where a downscaling approach is recommended (Yang *et al.*, 2010). In the improvement of GCMs, higher resolutions are provided by the regional climate models (RCM). Moreover, the coupled ocean-atmosphere general circulation models are being assessed in the Coupled Model Intercomparison Project (CMIP) in which CMIP plays a principal social role by supplying to the Intergovernmental Panel on Climate Change (IPCC) (Supharatid, 2015). In the rainfall assessments and monsoons in Asia, two models: the Asian Precipitation–Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE) and the Tropical Rainfall Measuring Mission (TRMM) simulated for precipitation, tropical cyclones, wind, and sea surface temperature (Promchote *et al.*, 2016). The global atmospheric general

circulation (AGCM) with the super high resolution of 20 km has been developed by the Japan Meteorological Agency (JMA) and the Meteorological Research Institute (MRI). MRI-AGCM3.1 and 3.2 outputs were extensively assigned for flood risk assessment and hydrological impacts in the Asia-Pacific region (Chaowiwat, 2012; Kure and Tebakari, 2012; Kwak *et al.*, 2012a). Regards to Chao Phraya River Basin, the GCM, the third and fifth phases of the Coupled Model Inter-comparison Project (CMIP3 and CMIP5), APHRODITE and TRMM, MRI-AGCM, and the Commonwealth Scientific and Industrial Research Organisation (CSIRO) have been simulated with hydrological models (Kure and Tebakari, 2012; Ogata *et al.*, 2012; Ligaray *et al.*, 2015; Supharatid, 2015; Promchote *et al.*, 2016). Each climate change model contributes to extreme rainfalls and implies that future rainfalls likely increase.

2.2.2 Policy Decision Making for Future Climate Change (d4PDF)

However, the question remains. Which climate change model is suitable to predict not only the extreme floods but also extreme droughts? The database for Policy Decision making for future climate change (d4PDF) was selected in this research due to its strengths and advances. Firstly, MRI-AGCM version 3.2 with high resolution, has been used in many researches, and results have confirmed an increase of future flood risk in CPRB (Kure and Tebakari, 2012). The MRI-AGCM3.2 is subsequently used to perform three sets of d4PDF that includes a historical climate simulation, a +4-K future climate simulation, and a non-warming simulation. Secondly, the sea surface temperature (SST) and sea ice concentration (SIC) are prescribed as the lower boundary conditions. Thirdly, global mean greenhouse gases and three-dimensional distributions of ozone and aerosols are also set as the external forcing (Hanittinan and Ichikawa, 2017). Fourthly, the

climatological warming patterns of six CMIP5 models are applied, covering the important uncertainties of internal and external variabilities from other models. Additionally, each ensemble as a set of CMIP5 model provides 15 ensemble members that are used by different initial conditions and SST perturbations (Mizuta *et al.*, 2017). These huge ensembles enable the assessment of future weather changes in sporadic rainfall events. Finally, the d4PDF has not been applied with local climate conditions and simulated in the hydrological model of CPRB. Only one research has studied a probability distribution function of the future river discharges at the Indochinese Peninsula, including CPRB (Hanittinan and Ichikawa, 2017). In combinations of the advantages of many models, improvements of uncertainties, and prediction of extreme events, the d4PDF is advisable for CPRB.

2.2.3 Post-processing Climate Change Data

The d4PDF, notwithstanding, does not take into account the local climatological conditions of the CPRB. Post-processes such as interpolation, statistical adjustments, and bias correction are needed before assessment of the climate impact due to the inherent bias between the d4PDF prediction and observation.

2.2.3.1 Interpolation

Global climate data are usually obtained at given stations in a series of grid cells. However, historical observed meteorological data are recorded at specific sites that are always different locations from the grid cells (Nalder and Wein, 1998). Particularly, interpolation is needed when the observed met-stations for meteorological observation are widely separated and limited. In general, the observation data from met-stations are

interpolated into point locations of model grid cells. Three major classification groups of interpolation methods are deterministic, probabilistic, and combined approaches.

The geometric characteristics of the observation locations are used to create a continuous surface by a deterministic method such as Nearest Neighborhood (NN) and triangulation, Inverse Distance Weighted Interpolation (IDW), Polynomial function (splines) and Linear regression (Li and Heap, 2008; Sluiter, 2009) as follows:

- The nearest neighborhood method assesses the value of the expected location from the nearest met-stations (*e.g.*, Thiessen polygon). The good performance of this method requires numerous nearest met-stations.
- The inverse distance weighted interpolation (IDW) is an advanced method of the nearest neighborhood. In the difference, the expected points are calculated by weights, in which the values are estimated *via* distances between the expected point and met-stations.
- The polynomial function method allocates the fitting trend functions of observations. Nevertheless, this method did not perform as well as kriging, linear regression models, and IDW, according to a series of comparisons (Sluiter, 2009).
- The linear regression method takes into account the effect of physical variables such as geographical coordinates and elevation (Tveito *et al.*, 2006). Moreover, Stahl *et al.* (2006) and Hofstra *et al.* (2008) have used multiple regression to involve latitude, longitude, elevation, and distance to coast as predictors.

The probabilistic method uses the concept of random samples, including the variance to predict the values in the interpolation process (Sluiter, 2009). In the probabilistic method, the variogram or semivariance is a significant concept that can contribute to several simple models, including Nugget, Exponential, Spherical, Gaussian, Linear, and

Power model (Li and Heap, 2008). The variogram is invariant when the expected location is further away from the range of applicability. Under the idea of the probabilistic method, numerous types of Kriging methods such as Ordinary Kriging, Co-kriging, Universal Kriging, Probability Kriging, and so on have been developed. The differences among these techniques are their assumptions. The co-kriging has a similar premise with the ordinary kriging method, and an additional assumption is to combine with the cross-variogram model. Probability Kriging was an advance assumption from the co-kriging in which the first and second variables are an indicator and untransformed data, respectively.

The advantages of these approaches, as mentioned above, have generally developed the combined procedures. They usually use the combination between spatial and statistical methods such as the Trend Surface Analysis combined with Kriging, Regression Tree combined with Kriging Regression, Regression Kriging, Gradient Plus Inverse Distance Squared Gradient, *etc.* In short, those interpolation methods can be applied to specific types of climate variabilities due to their assumptions, limitations, and data requirements.

Several methods are recommended. However, the difficulty, in order to select the interpolation method, is how to single out a suitable approach based on research objective(s) and accessible data (Li and Heap, 2008). The high number of observed meteorological stations in a study area and data accuracy are the main requirements for kriging methods. Moreover, it is important to consider the variation in the variogram models each month. In determining an optimum performance of the neighborhood approach, the data should be separated each month since the variogram model depends on temperature and precipitation, where the conditions vary by season (Nalder and Wein, 1998). Due to these requirements, only a handful of studies have been done by using the Kriging method for

CPRB (Supharatid, 2015). On the other hand, the IDW method is widely used for Thailand (Chaowiwat, 2012; Fujikura and Kawanishi, 2012; Tiengrod and Wongseree, 2013; Supharatid, 2015; Deeprasertkul, 2017). Valent and Vyleta (2015) have mentioned that the IDW method is one of the alternatives giving better estimates of areal rainfall even in places with rugged topography. The IDW produces an equally good representation of spatially distributed rainfall as compared to methods such as kriging or regression (Bhatti *et al.*, 2016). Also, the method was able to estimate the daily rainfall (Ahrens B., 2006; Bhatti *et al.*, 2016; Moeletsi *et al.*, 2016). However, the physical background of climatological variables, which are geographical coordinates, elevation, aspect, slope, *etc.*, could not be included in the IDW method (Tveito *et al.*, 2006). Gradient-plus-inverse-distance-squared (GIDS), which is a combined procedure between multiple linear regression and distance weighting, is considered to perform well in this research because the GIDS has an additional parameter of elevation. Also, multiple linear regression could be interpreted based on meteorological variables (Stahl *et al.*, 2006; Hofstra *et al.*, 2008). Nalder and Wein (1998) have examined the GIDS, four forms of kriging, inverse distance squared, and nearest neighbor methods. The results have shown that the GIDS had the best performance. Moreover, several researchers have recommended the GIDS because it is simple, robust, and provides an accurate interpolation (Nalder and Wein, 1998; Hofstra *et al.*, 2008; Kayıkçı and Kazanc, 2016). The approach is also applied for both precipitation and temperature at daily time-step, and it could overcome complex topography, *e.g.*, coastal, inland, and high-elevation (Koch and Coulston, 2004; Yue *et al.*, 2005; Hofstra *et al.*, 2008). In considering the use of interpolation for daily temperature, three aspects (elevation, characteristics of variation of air temperature, and prediction points) are essential factors. Thus, GIDS procedure

including these aspects has been proved to perform well at interpolating both daily maximum, minimum, and mean air temperatures in complicated geography such as Canada, Europe, China, and Turkey (Yue *et al.*, 2005; Stahl *et al.*, 2006; Hofstra *et al.*, 2008; Kayıkçı and Kazanc, 2016).

2.2.3.2 Bias Correction for Rainfall

Bias correction plays a significant role for an accurate climate change assessment that involves other impact studies, *e.g.*, hydrological models and ecosystems (Yue *et al.*, 2005; Yang *et al.*, 2010; Kure and Tebakari, 2012; Pierce *et al.*, 2015; Valdés-Pineda *et al.*, 2016; Switanek *et al.*, 2017). In the case of linear and non-linear models, bias correction methods consist of mainly five methods: linear scaling, elevation bias correction, power transformation, distribution transformation, and quantile mapping. These methods are generally to correct standard deviation and/or percentiles (Valdés-Pineda *et al.*, 2016). The linear and elevation bias correction methods correcting the variables of space and time are performed at a daily time step. In addition, the elevation bias correction has an assumption that similar error characteristics are allocated at the same elevation. However, the two methods do not address the temporal variability of rainfall (Gumindoga *et al.*, 2016). Regarding the non-linear bias correction, the power function has a purpose of correcting extreme values (*e.g.*, intensity and depth). In the power transformation method, monthly mean and standard deviation are input parameters by using the exponential form, which should be remembered for daily time-step use (Fang *et al.*, 2015). Tian *et al.* (2010) mentioned that the power function derived over and light rainfall intensities due to the over adjustment. The distribution transformation is to match the distribution function of observation into climate data which are adjusted by the mean

and standard deviation. However, in the assumption of the observation distribution function, it might introduce new biases. The quantile mapping method which is non-parametric applies all distributions of rainfall data. It could correct biases in mean, standard deviation, numbers of wet and dry days. Fang *et al.* (2015) and Gumindoga *et al.* (2016) have evaluated the performances of five bias correction methods; hence, their results found that the power transformation and quantile mapping are well-performing in correcting biases. Themeßl *et al.* (2011) have used two bias correction methods: the local intensity scaling (linear scaling) and the quantile mapping methods. The quantile mapping approach shows the best result, especially at the extreme rainfall events. Also, Valdés-Pineda *et al.* (2016) have advised that the quantile mapping approach is the key to the most effective in reproducing daily rainfall data.

The quantile mapping approach (QM) adjusts the cumulative distribution function (CDF) of observed and simulated rainfall data. The QM originates from the empirical cumulative distribution function (Bo'e *et al.*, 2007). The gamma distribution, which is a parametric model, is implemented with the cumulative distribution function (CDF) based on the assumption that the observed and simulated distributions are estimated by the gamma distribution (Piani *et al.*, 2010). This method could improve the mean and other limitations of the distribution, including droughts and heavy precipitation events. The gamma distribution method has been applied by Switanek *et al.* (2017). In their solution, the model rainfall value could be fitted and corresponded at a similar expectation of observed cumulative distribution function. Climate change may affect extreme precipitation events (*e.g.*, the amount of rainfall might be higher than historical means and extremes); however, these variabilities are not involved by the gamma distribution. To overcome the lack of climate change index, Yang *et al.* (2010) have improved the

prediction of extreme values by a combination of gamma and a general Pareto distribution (GPD). In regard to the advantages of the gamma distribution that has the ability to produce the asymmetrical and skewed distribution of daily rainfall in the scope of observed mean, the extremes above 95th percentile are referred to by a general Pareto distribution (GPD). Gutjahr and Heinemann (2013) have used the combination approach (Gamma and GDP method) in which they have mentioned that not only climate change signal is affected but also the number of dry days and mean rainfall are significantly reformed. As these have been improved to overcome the limitations, the Gamma and GDP methods are appropriate to correct the future climate change data in this research.

More specifically, since the gamma distribution is a parametric method, the estimation of parameters is essential in order to evaluate the cumulative distribution functions of both observation and model. Two parameters (shape and scale parameters) contribute to the distribution in which the shape parameter identifies the shape of the gamma distribution density functions in Figure 2.1. When the shape parameter is less than 1, the distribution is strongly skewed. When the parameter is equal to 1, it's the exponential distribution that it's exclusive gamma distribution. When the shape parameter is greater than 1, the gamma distribution originates at zero. The scale parameter affects to straighten or squash distribution function that moves from left to right by increasing the value of scale parameter. In order to estimate two parameters, the moment estimators approach is provided; however, this method is not recommended for large values of the shape parameter because it can generate unsatisfied results at the small values (Wilks, 2006). Maximum likelihood estimation is advised for well-performing approach (Yang *et al.*, 2010; Valdés-Pineda *et al.*, 2016; Switanek *et al.*, 2017).

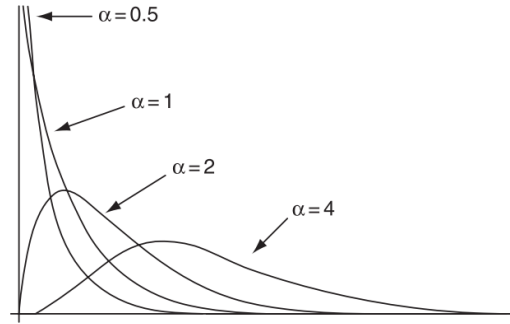


Figure 2.1 Gamma distribution density functions for four values of the shape parameter (α) from Wilks (2006)

In regard to the shape and scale parameters that have different values from the gamma distribution, a value of threshold and stability of parameter estimations is essential in the general Pareto distribution (GPD). After setting the value of the threshold, the parameters can be evaluated by the values above the threshold or block maxima approach (Coles, 2001).

2.2.3.3 Bias Correction for Air Temperature

Variations in temperature and precipitation generally depend on seasonality, geography, and topography. It is challenging to use a similar bias correction method with temperature when there is too much variability in different time scales of precipitation. The extreme tail value is not usually needed for temperature; however, the means are important to reduce biases of temperature data. Thus, in order to match the cumulative distribution function (CDF) of observed and model data, a transfer function as the quantile mapping methods, such as Cumulative Distribution Function-transform (CDF-t), CDF matching (CDFm), and equidistant CDF matching method (EDCDFm), are widely used. Noticeably, CDF-t and EDCDFm could not address extreme rainfall events and droughts.

On the other hand, both bias correction methods significantly change in means of daily temperature (Pierce *et al.*, 2015).

The CDF-t assumption is that a transformed function is established by the relationship between the CDF of the observed and model data (Flaounas *et al.*, 2013; Guo *et al.*, 2018). In order to perform an effective downscaling with the CDF-t model, the mathematical relation generated by the CDF-t model is temporally stable. It is important to note that the CDF-t has been calibrated without distinction between the seasons. In regard to the CDFm assumption, only historical model distribution applies to the future period. Maintaining matches of observations into the models are an advantage of this method; in contrast, the historical temperature distribution does not change much (Li *et al.*, 2010). EDCDFm is a developed method from the previous two approaches in which the difference between the observed and model values during training period also applies to the future period. Moreover, the CDFs of the historical and future periods are also involved. Guo *et al.* (2018) have applied CDF-t and EDCDFm approaches in China, and they mentioned that both ways improved model performance significantly. In their investigation, the results show that the temperature CDF curve of EDCDFm method is closer to the observation than the CDF-t method. Also, Li *et al.* (2010) and Wang and Chen (2014) concluded that the EDCDFm method is an advanced traditional CDF method, particularly for temperature bias correction.

2.3 Strategies of Water Resource Management

To meet conflicting water demand and to reduce the frequency and risks of floods and droughts, water resources integration and sustainable management are challenging (Loucks and Beek, 2017). Ponds are an important small scale of water resources to meet

water demand, particularly for agriculture irrigation. In considering the large scale, a reservoir can serve multi-purposes not only water supply but also flood protection, drought mitigation, and hydro-electrical generation. In this section, significant information and operation of both pond and reservoir are provided.

2.3.1 Pond Management

Ponds are a common water supply for a variety of activities, such as irrigation and farming. Furthermore, ponds provide human recreation, wildlife habitat, fish production, erosion control, *etc* (Austin *et al.*, 1996). Agricultural uses are the main purpose of ponds in Thailand due to its high water demands, groundwater use mitigation, and economical water resource in recent years. Focusing on crop irrigation demand and pond water availability, appropriate pond planning and construction are required.

2.3.1.1 Considerations of Pond Construction

Embankment and excavated ponds are the typical pond constructions depending on pond size, depth, soil, location, land-use, water demand, other characteristics of an area (USDA, 1997). Austin *et al.* (1996) have recommended minimum size and depth of ponds for Ohio in USA due to the seasonality in the prevention of winter snow, fish habitats, local soil conditions. They mentioned that about 2.4 m should be maintained for minimum depth. Additionally, site and climate characteristics of a pond are general considerations prior to the final design and construction. Proper pond site should be located in drainage areas to maintain water in ponds during the dry season and drought events. Increasing drainage areas can rise extreme runoffs affected to pond water level (USDA, 1997).

The pond capacity plays essential role to meet water requirements. Rainfall, runoffs, seepage rate, and evaporation losses are estimated to be sure that water storage is enough for water uses. A sample method is advised to calculate pond capacity by multiply pond surface area with 0.4 times and maximum water depth (USDA, 1997). This method, however, is not applicable and reliable. Estimating storm runoff method is guided because soil types, vegetation, land-use, infiltration are taken into account in the calculation of storm runoff volume using the runoff curve numbers (USDA, 1997). In pond design and construction, pond capacity can be estimated by a combination of four parameters (effluent production, stormwater, rainfall, and freeboard). The effluent production is the water uses for crops and other functions. The stormwater is the amount of rainfall-runoff that is calculated by the storm runoff method or evaluation of 90th percentile rainfall multiplied with pond basin. The rainfall onto the pond surface is computed at 90th percentile rainfall. Finally, the overflow protection, called freeboard, associated flood mitigation should be considered to capture future maximum pond water level. The freeboard is designed to cope with the tail-rainfall into ponds. Required 0.6 m. freeboard on the storage pond is recommended being an engineering safety factor (McDonald, 2009).

2.3.1.2 Environmental Impacts Related to Pond Construction and Management

In order to minimize aqua-cultural problems and adverse environmental effects in ponds, pond shape is suggested to construct long rectangular shape because it's easier to de-sludge than a square shape. Pond depth over 3 m is not advised because it can generate an anaerobic process at the bottom. For the effective pond, it is recommended to keep 0.5

m of water level in the pond since the bottom can be protected from cracking and reseeded. The pond should be dried up every 2-3 years to mitigate high salinity concentration (Barrie, 2008; McDonald, 2009). In regard to aqua-cultural pond, pond water level should be maintained about 1-1.5 m and pond depth is recommended to construct at 2 m (Kam *et al.*, 2002).

Variation of depth affects water quality in general. In upper layers, photosynthesis occurs due to light penetration in the day, which changes the pH value and the concentrations of dissolved oxygen and carbon dioxide. Dissolved oxygen concentrations increase while the carbon dioxide concentrations decrease with changes of pH (Sallenave, 2012). Increasing with depth, concentrations of ammonia, nitrite, hydrogen sulfide, carbon dioxide, productions of decomposition, and anaerobic metabolism tend to increase due to the anaerobic processes at pond bottom (Boyd and Tucker, 1998). Additionally, an important pond water quality parameter is organic matter, *e.g.*, suspended solids. Sediment loads are generally from runoffs, erosions of pond embankments, and deaths of phytoplankton and other cells (Shelton and Boyd, 1993). Focusing on issues of ponds in Thailand, since atmospheric temperature increases from March, water temperature is rising while dissolved oxygen concentration reduces. Due to the low concentration of dissolved oxygen, anaerobic bacteria activities produce methane and hydrogen sulfide gases that generate rotten egg smells (Srisuwantach *et al.*, 1981).

Consequently, the water quality should be improved as following the water quality treatment in the pond management guideline (Austin *et al.*, 1996). Boyd and Tucker (1998) have provided mainly five water quality management approaches: protecting ponds from external sources of pollution, drying pond bottoms regularly to increase decompositions, using liming to balance total alkalinity in acidic water in ponds,

increasing dissolved oxygen by aeration, and exchanging water in ponds to reduce excessive nutrients and toxic substances.

2.3.1.3 Pond Designs and Impacts on Watershed

Due to the impact of stormwater, ponds are a scheme of a drainage system. Ponds require relatively low maintenance and provide efficient water resources and irrigation. Moreover, ponds reduce potential flood and attenuate peak flows of the hydrograph. In terms of flow characteristics, optimal pond designs have been obtained for multiple pond geometries and locations (Tsavdaris *et al.*, 2015). Reducing flood risk and erosion on downstream of the ponds are the main findings. An elliptical-shaped pond system is the most appropriate pond design for flood risk management and sedimentation control. It is necessary to consider physical, hydrological, geometric, and dynamic conditions for pond design. Khan *et al.* (2013) has suggested that without any of these conditions, it may lead to negative impacts on the flow regime. Additionally, natural flow characteristics depend on several components such as magnitude, frequency, duration, and timing of rainfall events and runoffs (Rytwinski *et al.*, 2017). Maximum runoff and rainfall, including its duration, should be taken into account with the pond's inflow and outflow, where the pond design and size can be determined (Hong, 2008).

2.3.1.4 Developments in Pond Modelling

As mentioned above, in order to understand the flow patterns in ponds, simulation models can be a solution (Tsavdaris *et al.*, 2015). The benefits of modelling are to enable the simulation of the flow in the pond before the real construction and to provide more information about flow patterns (Khan *et al.*, 2013). Due to the essential model uses, a water budget simulation model is provided for the purpose of estimating water

requirements for agriculture pond. The model involves regulated inflow, precipitation, runoff, evaporation, seepage, effluent discharge, and overflow in the forecasting calculation (Nath and Boite, 1998). In regard to alternative objectives, Ouyang *et al.* (2016) has established a Structural Thinking, Experimental Learning Laboratory with Animation (STELLA) model. They have estimated the ratio of on-farm water storage pond size by investigating pond hydrological processes and pond water for irrigation. The results showed that dramatically changes in pond water level are caused by using water for irrigation, and a reasonable ratio is suggested for crop irrigation purposes. Simultaneously, the STELLA model has been developed to estimate additional factors that include water budget of a pond and more advanced irrigation systems. Consequently, the model has proved to be a practical tool to evaluate pond water budget and irrigation for crops (Ouyang *et al.*, 2017). The STELLA model combined with Pond-Irrigation Model (PIM) was improved to determine an optimal farm-pond ratio to meet water requirements for crop irrigation (Ouyang *et al.*, 2018).

2.3.2 Reservoir Operations

For effective water management, future water discharges of a reservoir should be determined based on conditions of available water in the dam, water demands from the downstream, and hydrological situations. At different times and hydrological characteristics, the dam is operated under different regulations between dry and wet seasons in general.

2.3.2.1 Reservoir Purposes and Operations

Reservoirs are key in water resource management, particularly flood management and drought control. They help reduce flood risks by attenuating the flood peaks. The

reservoirs should be operated by taking into account the frequency, timing, and duration of floods. In wet seasons, high inflow, low water demand, flood protection, and water supply for next dry season are significant factors to decide reservoir water releases. Within available water in the reservoirs, water demands, environmental conditions, and water utilization are parameters of reservoir water discharges during low flows (WEC, 2008). To moderate the flow, it is important to understand the special characteristics, purposes, and capacity of the reservoir. For small and moderate flows, the reservoirs store water to decrease discharge at downstream while space is necessitated for coming floods. These operations can be achieved by identifying maximum and minimum reservoir water levels. To meet the water requirements from the agricultural sector, water utilization, industrial uses, *etc.*, reservoirs are desirable to store water in rainy season for the usage in dry seasons. Additionally, hydropower generation is an exclusive objective of the large-scale reservoir to provide green energy at a low cost. The preliminary decision of minimum reservoir discharge also bases on the benefits of hydropower generation (US Department of the Interior, 1987). In contrast, reservoir operations for flood management aim to reduce flood risks and to mitigate losses. The combination of structural and non-structural measures which are rule curves and spillways, respectively, is necessary for effective operations during flood events (WEC, 2008).

2.3.2.2 Applications in Reservoir System Operation

Reservoir operation often involves complex variables such as inflows, return flows, evaporation, storages, diversions, discharge, hydro-electric power generation, irrigation, and water demands. To achieve the complexity, development of reservoir operation modelling is required with considerations of the reservoir's purposes, capacity, effective

performance, maximum benefits, and minimum costs. Multi-objectives and climatological variabilities are important parameters of real-time and long-term reservoir operation models (Rani and Moreira, 2010). Simulation, optimization, and combined simulation-optimization modelling approaches are used in reservoir operation studies. The simulation algorithm stands on water balance equation using hydrological conditions, inflows and other operations. The optimization approach uses very long hydrological data to obtain the optimal reservoir operation. Numerous techniques, *e.g.*, linear programming, non-linear programming, dynamic programming, computational intelligence, large scale optimization techniques, and multi-objective optimization involve in the optimization technique. Linear programming is a flexible application for large scale problems; however, its usage is limited to nonlinearity of some reservoir operations. The non-linear programming overcomes complicated relations of physical and hydrological variables. Dynamic programming solves complex multi-stage problems and discontinuous functions such as time and non-linear issues. The fuzzy logic theory is also included in the dynamic programming based on stochastic variables because this method resolves uncertainty problems (*e.g.*, future inflow and storage) to obtain optimal reservoir operation (Fullér, 2000). In order to deal with restrictions of traditional optimization methods, computational intelligence is a solution such as artificial neural networks (ANN) and adaptive network-based fuzzy inference system (ANFIS). The combined simulation-optimization modelling approaches aim to accomplish complicated multi-reservoir systems by using the benefits of both algorithms (Rani and Moreira, 2010).

2.3.2.3 Adaptive Network-based Fuzzy Inference System (ANFIS)

Due to the complicated criteria, prediction of future water discharge is recommended to use computing techniques such as Fuzzy logic, adaptive network-based fuzzy inference system (ANFIS) and Artificial Neural Network (ANN) (Mehta and Jain, 2009). Each technique has pros and cons. The ANN has struggled in constructing a suitable training algorithm. The fuzzy logic has mentioned for effective performance in handling uncertainty, non-linear and noisy data (Jothiprakash and Magar, 2012). However, difficulties as required expert knowledge to design fuzzy logic rules in order to construct fuzzy modelling have been discussed (Jang J.S.R., 1993). To overcome this problem, the Neuro-Fuzzy System is becoming more popular due to using the neural network to learn algorithms and using the fuzzy system to match input variables associated with output(s) (Fullér, 2000; Chang and Chang, 2006). By using the Neuro-Fuzzy system, the inputs to be tuned in the ANFIS model play essential rules to improve model performance. To simulate reservoir water discharge or storage, two algorithms; simulation-based and optimization-based algorithms are major uses in reservoir operation models. The simulation-based algorithms require observed information. These schemes have been introduced to use storage capacity, inflow, and downstream water demand as input variables (Hanasaki *et al.*, 2006; Coerver *et al.*, 2018). Additionally, the optimization-based algorithms require extreme future inflows, rainfalls, and water demands to decide optimal water discharge and effective reservoir operations (Loucks and Beek, 2017; Coerver *et al.*, 2018).

2.4 Summary

Applications of hydrological models were reviewed in terms of pros and cons. In considerations for the flexible adjustments in wide ranges of parameter values, model modules based on basin characteristics, well-performance for daily discharge, and river discharge simulation of large basins, the Hydrological Simulation Program-Fortran (HSPF) has shown to be a desirable choice for the CPRB.

The predictions of future climate *via* numerous climate change models (GCM, RCM, CMIP, APHRODITE, TRMM, AGCM, *etc.*) have been applied with hydrological models for the CPRB. Those models also imply that future rainfalls likely increase. Given the objectives of this research in order to predict not only the extreme floods but also extreme droughts, the database for Policy Decision making for future climate change (d4PDF) was selected due to 4-degree Celsius increase of future climate simulation and advantages of many previous models. In addition, the d4PDF has not been applied with local climate conditions and simulated in the hydrological model of the CPRB. In order to address global climate data under local conditions, the methods of interpolation and bias correction are key post-processing techniques. Interpolation methods are classified into deterministic (Nearest Neighborhood, Inverse Distance Weighted Interpolation, *etc.*), probabilistic (numerous types of Kriging methods), and combined approaches (Regression Kriging, Gradient-plus-inverse-distance-squared (GIDS), *etc.*). Their assumptions, limitations, and data requirements were introduced. The GIDS, which is a combined procedure between multiple linear regression and distance weighting, was considered to perform in this research because the method includes the physical background of climatological variables and provides an accurate interpolation. For the

bias correction approach, the quantile mapping (QM) approach is the most effective in reproducing daily rainfall and air temperature data. The QM approach for rainfall consists of mainly three methods: the empirical cumulative distribution function, the gamma distribution, and the combination of gamma distribution and general Pareto distribution (Gamma and GDP method). However, the empirical cumulative distribution function and the gamma distribution could not improve the prediction of extreme rainfall events and droughts. Since the Gamma and GDP method could overcome the limitations, the combined method is appropriate to correct the future climate change data. Due to the different patterns between rainfall and temperature, the bias correction methods used for precipitation could not be applied to the temperature. The bias correction approaches for temperature using the developments of the cumulative distribution function (CDF) were considered by their assumptions. The Equidistant Cumulative Distribution Function Matching (EDCDFm) is the best choice because observed and modelled distributions during a training period are applied into the future period.

Strategies of water resources management focusing on pond management and reservoir operation were introduced. Since agricultural uses are the main purpose of ponds in Thailand, pond capacity plays an essential role to meet crop water requirements. In considerations of pond construction, rainfall, runoffs, seepage rate, and evaporation losses are estimated to be sure that water storage is enough for water uses. In addition, seepage, effluent discharge for irrigation, and overflow should be involved in the pond modelling in order to optimal farm-pond capacity. In general, the reservoir operation is based on several variables, *e.g.*, available water in dams, water demand from the downstream, and unsystematic hydrological situations. Due to the complicated criteria, it is recommended to use computing techniques such as Fuzzy logic, Adaptive Neuro-Fuzzy Inference

System (ANFIS), and Artificial Neural Network to predict the water discharge in the future. The fuzzy logic theory is alternative modelling because this method resolves uncertainty problems (*e.g.*, future inflow and storage). However, difficulties as required expert knowledge to design fuzzy logic rules in order to construct fuzzy modelling were mentioned. The ANFIS, which uses the neural network to learn algorithm and the fuzzy system to match input variables associated with output(s), was selected to accomplish complicated multi-reservoir systems for Bhumibol and Sirikit Dams.

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Chapter 3

Mitigating floods *via* Integrated Watershed

Management using HSPF

3.1 Introduction

Due to the extreme flood experience in Thailand in 2011, over 12 million people were affected with 728 deaths as well as 16,669 km² of damaged agricultural areas and a loss of USD 46.5 billion during a couple of months of paralyzed inundation (Poapongsakorn and Meethom, 2012; World Bank, 2012). After these impacts, the reasons of the well-known flood were discussed in the view of rainfall and dam operation. Evident references have recorded that the total rainfall intensified by 43 percent in comparison to the average rainfall of the rainy season during the 1982-2002 period (Komori *et al.*, 2012). By cause of the five storms, flash floods and landslides occurred with accelerated water replenishments in large-scale dams, including both Bhumibol Dam and Sirikit Dam (Aon, 2012; Bidorn *et al.*, 2015). Since two tropical cyclones suddenly increased the water levels in both dams in October, the levels reached the maximum storage of Bhumibol Dam. Consequently, there was an immediate discharge of a high-water amount. Thenceforth, the Lower Chao Phraya River Basin (CPRB) was flooded, and numerous floodgates collapsed by the high-water pressure. Encompass with the causes, the dam operation took the most blame for the devastating impacts. Many people believed that decision-makers should adapt a different operation scheme during the flood period. In

order to provide the plans and policies of integrated flood management and water resource management, scientific analysis tools need to contribute into the framework of decision making.

By climate change in precipitation, hydrological processes are mainly affected. In order to understand impacts of extreme rainfalls and flood risk management on flow regime, a hydrological model is a solution. As information in Chapter 2, Hydrological Simulation Program-Fortran (HSPF) is the most suitable betterment, in which the model comprises three modules: pervious land, impervious land and reaches in a sub-basin (Bicknell *et al.*, 2001; Reed *et al.*, 2004; Ryu *et al.*, 2009). Additionally, the model offers a possibility to evaluate the impacts of dam operation during stream flow. Even for a large basin area of 500,000 km², the flow regime was also achieved for watershed simulation using HSPF (Hayashi *et al.*, 2004). Consequently, the HSPF is a desirable choice to simulate river discharge for a large basin like the CPRB, which has an area over 150,000 km².

With the results above and further purposes in Chapter 7, this chapter aims to apply a Hydrological Simulation Program-Fortran (HSPF) model for Chao Phraya River Basin in consideration of basin characteristics. Moreover, the model is used to simulate additional two objectives: thinking over dam operation and other approaches for flood mitigation. The second objective is to answer how the effect of a “different decision” on existing dam operation during the 2011 flood, which had never been absolutely explored. Accordingly, the different releases storage ratios and the timing of water releasing decisions from Bhumibol Dam and Sirikit Dam are simulated to explore applicable dam operation. Furthermore, due to the impediment of structural measures in the Master Plan as described in Chapter 1, detention pond projects are also one existing solution of integrated

watershed management. As a consequence, a third objective is to examine the potential flood prevention by integrated watershed management. This management is combined by the advisable dam operation and detention ponds (Monkey's Cheek projects) with investigating the proposed retarding basins by Thai Master Plan and the suggested new Monkey's Cheek project.

3.2 Current Water Resource Management

3.2.1 Upstream Dams and Irrigation Projects

Bhumibol Dam (BD) and Sirikit Dam (SD) exclusively associated with irrigation purpose include two projects on the downstream of Ping River Basin and four projects on the downstream of Yom and Nan River Basins as more information was provided in Chapter 1. There are 30 projects in total, which collectively constitute a complicated operating system in the lower part of the basin. These irrigation projects are mainly to support water for agricultural areas.

3.2.2 Monkey's Cheek Projects

Given the characteristics and topography of CPRB, the detention ponds or Monkey's Cheek projects inventively proposed by His Majesty King Bhumibol Adulyadej are necessary structural measures for flood protection. The projects, however, have contradistinctive managements; taking into account environmental, social, and traditional aspects of each area. In the Upper CPRB, they provide not only flood and drought protection but are also of relevance for the rice cultivations. The peak flow and overflow

can be debilitated as temporary storage during the rainy season, and rice could be cultivated at the artificial wetlands during the dry season (MOAC and JICA, 2009).

3.3 Materials and Methods

3.3.1 Data Collection

A Digital Elevation Model (DEM) used for sub-basin and stream delineation was originally acquired from HydroSHEDs of US. Geological Survey (from <https://hydrosheds.cr.usgs.gov/dataavail.php>). The data requirement used for HSPF model setup is secondary data, which were obtained from several Thai government agencies. Hydro-meteorological data (rainfall, maximum temperature, and minimum temperature), land use, and daily data of water inflow and water outflow at dams were successfully received from Thai Meteorological Department (TMD), Land Development Department (LDD) and Electricity Generating Authority of Thailand (EGAT), respectively. Rating curve, cross-section and daily discharge of rivers, which are noteworthy influences on model setup and comparisons, were procured from Royal Irrigation Department (RID).

The daily time series data of rainfall, maximum and minimum temperatures were prepared *via* SARA Timeseries Utility. Daily potential evapotranspiration (PET) data were also computed by the tool using Hamon PET method, in which monthly coefficients, latitude, daily maximum air temperature, and minimum air temperature were used in the calculation. More specific rainfall data preparation, the limited coverage of 22 rain gauge stations are available in the study area. According to the mean rainfall over the basin,

interpolation using Thiessen Polygon method was used to determine relevant rainfall weights across the area (Fiedler, 2003; Eruola *et al.*, 2015).

In respect to Land use data, the utilized information was gained from the 2008-2009 data. Within the consideration of objectives, the land-use was re-classified into five types: including agriculture, forest, paddy field, water body, and urban area. In particular, the landscape of the northern region consists of mountainous areas and steep slopes. According to the area characteristics, agricultural area and forest cover about 13-40% and 14-42% of the Upper CPRB area, respectively. The Lower CPRB is mainly covered by paddy fields (23-40% of the total area) because of the floodplain characteristics and the local weather.

3.3.2 Model Setup

In order to set up the model as follow the realistic situation of basin's characteristics, hydraulic attributes and irrigation systems were applied with parameter's adjustments as shown in Figure 3.1.

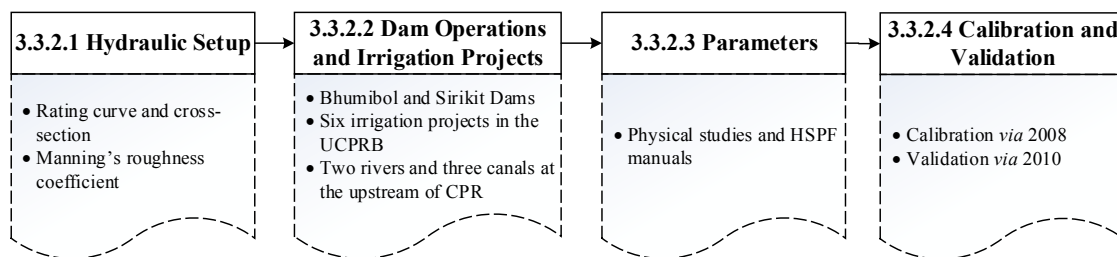


Figure 3.1 Framework of the model setup

3.3.2.1 Hydraulic Setup

Setting up the hydraulic attributes of the stream network such as river geometry, flow velocity, *etc.* is of particular importance. For HSPF, a matrix-like set-up file known as Hydraulic Function Tables (FTABLES) is used to define river stage, surface area, water volume, and outflow. Data collected from 34 river gauge stations were used to set FTABLES. An important factor in additionally defining the relationship between river stage and outflow is the Manning's roughness coefficient (n). The Ping River, Wang River, Yom River, and Nan River were defined for the Manning's roughness coefficient from 0.03-0.05 depending on steep slope and elevation of the areas. For the floodplain area and the Lower Chao Phraya River Basin, the roughness coefficient was defined in the value range of 0.05-0.07 (Chow *et al.*, 1988; Visutimeetegorn *et al.*, 2006; Korichi and Hazzab, 2012).

3.3.2.2 Dam Operations and Irrigation Projects

Dam operations are an irrigation technique for flood mitigation and water storage in the basin. Bhumibol Dam (BD) and Sirikit Dam (SD) are large reservoirs that influence the hydrological features in the basin (Tebakari *et al.*, 2012). These two major dams are operated by considering the historical daily flow rate data. Thai government considers the CPRB as a priority water resource; as such several major irrigation projects were being conducted across the area. Six irrigation projects (Pay Sumpol, Dong Sathtee, Tha buay, Narei Suan Dam, Kampaengphet and Nakhon Sawan projects) were constructed for Ping, Nan and Yom River Basins. The water withdrawn from upstream of Chao Phraya River *via* two rivers (Tha Chin River and Noi River) and three irrigation canals were also taken into account to estimate water intakes in the model as shown in Figure 3.2. The decreased

capacity of Yom River constitutes as one of the major causes of floods, leading to the construction of multiple irrigation projects in recent years. Therefore, the irrigation canals, which withdraw water from Yom River, then transfer it to Nan River and seven detention ponds as temporary storage during the rainy season, have been applied in a special action module of HSPF.

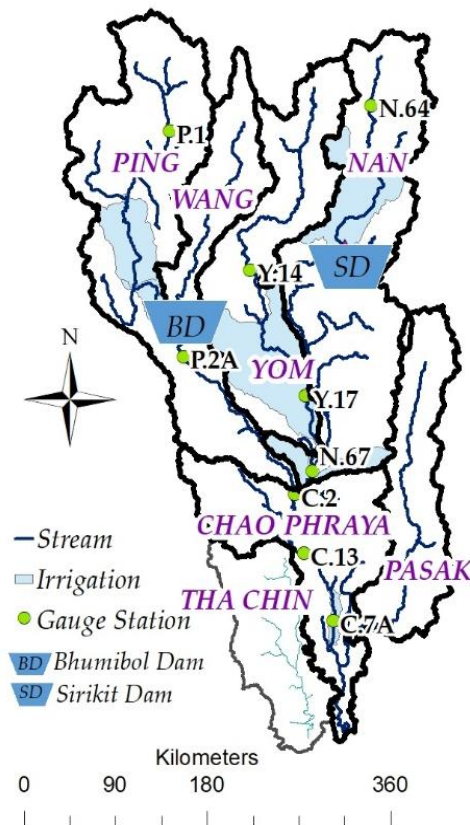


Figure 3.2 Boundary of Chao Phraya River Basin and the areas of setting irrigation projects in the model

3.3.2.3 Parameters

The parameters are taken from several physical studies and HSPF manuals, which are summarized in Table 3.1. More specifically, parameters representing the paddy field characteristics are of equal importance for the set of parameters given the predominance of this land coverage across the basin. In particular, terraced paddy fields with steep slopes,

which are popular in the northern part of the country, have lower Infiltration Capacity (INFILT) values than the ones found along the southern deltas. In agricultural areas, each sub-basin has several different vegetation, such as longan trees in northern Thailand, sugarcane in east-central Thailand, and durian and mango trees in central Thailand. Interception Storage Capacity (CEPSC) and Manning's n for the overland flow plane (NSUR) also relate to land cover types. The different canopy characteristics were also considered to adjust the LZSN, CEPSC, and NSUR parameters for each sub-basin.

Table 3.1 Hydrological Parameters

Parameter	Unit	Description	Value												Reference
			Agriculture			Forest			Paddy field			Water			
			1000-2500 MSL	100-1000 MSL	0-100 MSL	1000-2500 MSL	100-1000 MSL	0-100 MSL	1000-2500 MSL	100-1000 MSL	0-100 MSL	1000-2500 MSL	100-1000 MSL	0-100 MSL	
INFILT	mm/h	Index to infiltration Capacity	600-750	500-600	350-450	1100-1400	950-1100	700-900	120-150	150-200	200-270	8.5-15	6-7.5	4-5.5	Solomon, 2005
LZSN	mm	Lower zone nominal storage	150-200	200-230	240-270	300-500	230-270	200-230	150-220	150-170	150-200	7.5-10	7.5-10	7.5-12	Gao et al., 2014
IRC		Interflow recession parameter	0.4-0.6	0.5-0.7	0.7-0.8	0.3-0.6	0.5-0.8	0.6-0.8	0.4-0.7	0.5-0.8	0.6-0.8		0.4		USEPA, 2000
CEPSC	mm	Interception storage capacity		0.5-2			2-2.5			1.2			0.01		Solomon,2005
NSUR		Manning's N for the overland flow plane		0.08-1.9			0.2-0.3			0.3			0.011-0.07		Solomon,2005
LZETP	none	Lower zone E-T parameter; the density of deep rooted vegetation		0.4-0.6			0.6-0.7			0.2-0.4			0.1		USEPA, 2000
UZSN	mm	Upper zone nominal soil moisture storage					0.25-45						8.0-17		Ryu, 2009
AGWETP		Fraction of remaining ET from active GW					0.05-0.2						0.6		USEPA, 2000
BASETP	none	Fraction of potential evapotranspiration from baseflow					0.03-0.7						0.01		USEPA, 2000
INTFW	none	Interflow inflow parameter						1-18.0							USEPA, 2000
AGWRC	day-1	Daily recession constant of groundwater flow						0.944-0.999							USEPA, 2000
INFEXP		Exponent in infiltration equation						1-2.0							USEPA, 2000
INFILD		Ratio of max/mean infiltration capacities						1.5-2.0							USEPA, 2000

*MSL: Mean sea level

3.3.2.4 Calibration and Validation

The hydrological model was calibrated and validated with the observed river discharge data of 2008 and 2010. The quantitative assessments of those results were done

through Nash-Sutcliffe efficiency (NSE), RMSE-observation standard deviation ratio (RSR) and coefficient of determination (R^2) (Fonseca *et al.*, 2014; Ribarova *et al.*, 2008).

3.3.3 Simulations

Regarding the scenarios, the river discharge in 2011 was simulated prior to changing several conditions. Since the political pressure on the mismanagement of large-scale dams was being debated, scenarios of dam operation for a considerable approach during flood conditions were set up. There are two main scenarios in this chapter, dam operation and detention ponds. The scenarios of detention ponds consist of the Thai Master Plan projects and a new Monkey's cheek project, which were established to explore the possible flood prevention.

3.3.3.1 Dam Operation

Dam operation is a non-structural intervention, yet plays an essential role in keeping the water demands meet, fueling economic activities, and as well mitigating floods and droughts. In flood management, the release storage ratios are one pivotal option of dam operation roles to control the water release related to the current water storage of the dam. The impacts of the dam operations on the flood peaks in 2011 are also considered for water release and timing decisions. The water release calculation is done through a general reservoir water balance in Equation 3.1. More specifically, storage at the next time interval (S_{t+1}) is computed by inflow (Q_t), rainfall (R_t), evaporation (E_t), and the storage at the current time interval (S_t) (Maidment, 1993).

$$S_{t+1} = S_t + Q_t + R_t - O_t - E_t \quad (3.1)$$

The released water (O_t), accordingly, is calculated by the storage at the current time interval (S_t) multiplied with the daily release storage ratio (r) as changes of the ratios shown in the Table 3.2. The daily release storage ratios are considered by the storage classifications of high, normal, low, and very low water levels. During the high-water level, the high rainfall intensity is taken into account by releasing only a small scale of water to prevent overflows at downstream of the dams. Within the scope of purpose for the timing of water releasing decisions, more amount of water was controlled to discharge in September for scenario S.1, August for scenarios S.2-S.4 and July for scenarios S.5-S.8.

Table 3.2 Scenarios for daily release storage ratio (r)

Scenario	Bhumibol Dam										Sirikit Dam									
	July to August					September to November					July to August					September to November				
	$S_t > 10000$		8000< S_t <100000	6500< S_t <8000	$S_t < 6500$	$S_t > 10000$		8000< S_t <100000	6500< S_t <8000	$S_t < 6500$	$S_t > 8000$		6000< S_t <8000	4000< S_t <6000	$S_t < 4000$	$S_t > 8000$		6000< S_t <8000	4000< S_t <6000	$S_t < 4000$
	$R_t > 50$ mm	$R_t < 50$ mm				$R_t > 50$ mm	$R_t < 50$ mm				$R_t > 50$ mm	$R_t < 50$ mm				$R_t > 50$ mm	$R_t < 50$ mm			
S1 Sept	-					0.0035	0.005	0.003			-					0.001	0.0005	0.005	0.003	
S2 Aug	0.008	0.008	0.007			0.003	0.003	0.002			0.008	0.008	0.007		0.001	0.003	0.003	0.002		
S3 Aug	0.007	0.006	0.007			0.0025	0.0025	0.002			0.007	0.008	0.007		0.001	0.002	0.002	0.002		
S4 Aug	0.007	0.007	0.007			0.002	0.002	0.002			0.008	0.008	0.007		0.0005	0.001	0.002	0.002		
S5	0.007	0.007	0.007			0.003	0.003	0.002			0.007	0.007	0.007		0.001	0.003	0.003	0.002		
S6	0.007	0.007	0.007			0.002	0.002	0.002			0.007	0.007	0.007		0.001	0.002	0.002	0.002		
S7	0.006	0.006	0.006			0.002	0.002	0.002			0.006	0.006	0.006		0.001	0.002	0.002	0.002		
S8	0.008	0.008	0.007			0.001	0.001	0.001			0.008	0.008	0.007		0.001	0.001	0.001	0.001		

In order to ensure the impacts of considerable dam operation on river discharges, the appropriate approach was tested under different hydrological regimes. The daily river discharges at the gauge station C.2, accordingly, were simulated with and without the underlying scenario under three conditions that are a flood situation of the year 2006, the normal hydrological regime of the period 2007-2010, and a drought situation of the year 2014.

3.3.3.2 Detention Ponds (Monkey's Cheek Projects)

A. Master Plan Projects

After the experience of the flood 2011, the Thai Master Plan on Water Resource Management Report proposed the use of retarding basin and retention areas in the Upper CPRB to mitigate further floods (SCWRM *et al.*, 2012). Five projects on the east and west sides of Tha Bau district, in the southern and northern parts of Dong Set Thi district, and in the Phai Chum Phon district were proposed to handle the 1,161 million cubic meters of water in Figure 3.3(a). To estimate the effects on the floods, the Mater Plan projects, the scenarios P.0-P.3 in Table 3.3, were need to examine those impacts on the flood peaks of the year 2011.

B. Suggested new Monkey's Cheek Project

Due to the high overflow volume downstream of Nan River, an additional detention pond, the Monkey's Cheek project, was suggested to be constructed. Given more information, an appropriate location would be the surroundings of the Bung Boraphet Wetland, in Figure 3.3, because of several suitabilities. Firstly, the wetland is located at the flood risk area, in Figure 3.3(a), where the overflow usually occurs; additionally, the main soil type of the area's foundation is clay resulting in an area which is inundated due to low infiltration rate and poor drainage. Secondly, the wetland is operated by Thai Fisheries Department, Department of National Park, Wildlife and Plant Conservation, and Royal Irrigation Department. Because of the government's management, political pressure from social aspects could be damped out if the area is selected to be the Monkey's Cheek project. Finally, the area of interest is covered by 13 percent of water body and 87 percent of paddy field as shown in Figure 3.3(b). The rice cultivation follows

the project concept by cutting the flow peaks during the rainy season and releasing water from the project during the dry season so that the farmers could cultivate the rice at least one time a year for the off-seasonal rice when the water level is low as a temporary wetland. The land use in the wetland, however, is limited due to several species of bird; accordingly, the Department of National Park, Wildlife and Plant Conservation enacted a conservation law for the protected area represented by a grey line in Figure 3.3(b).

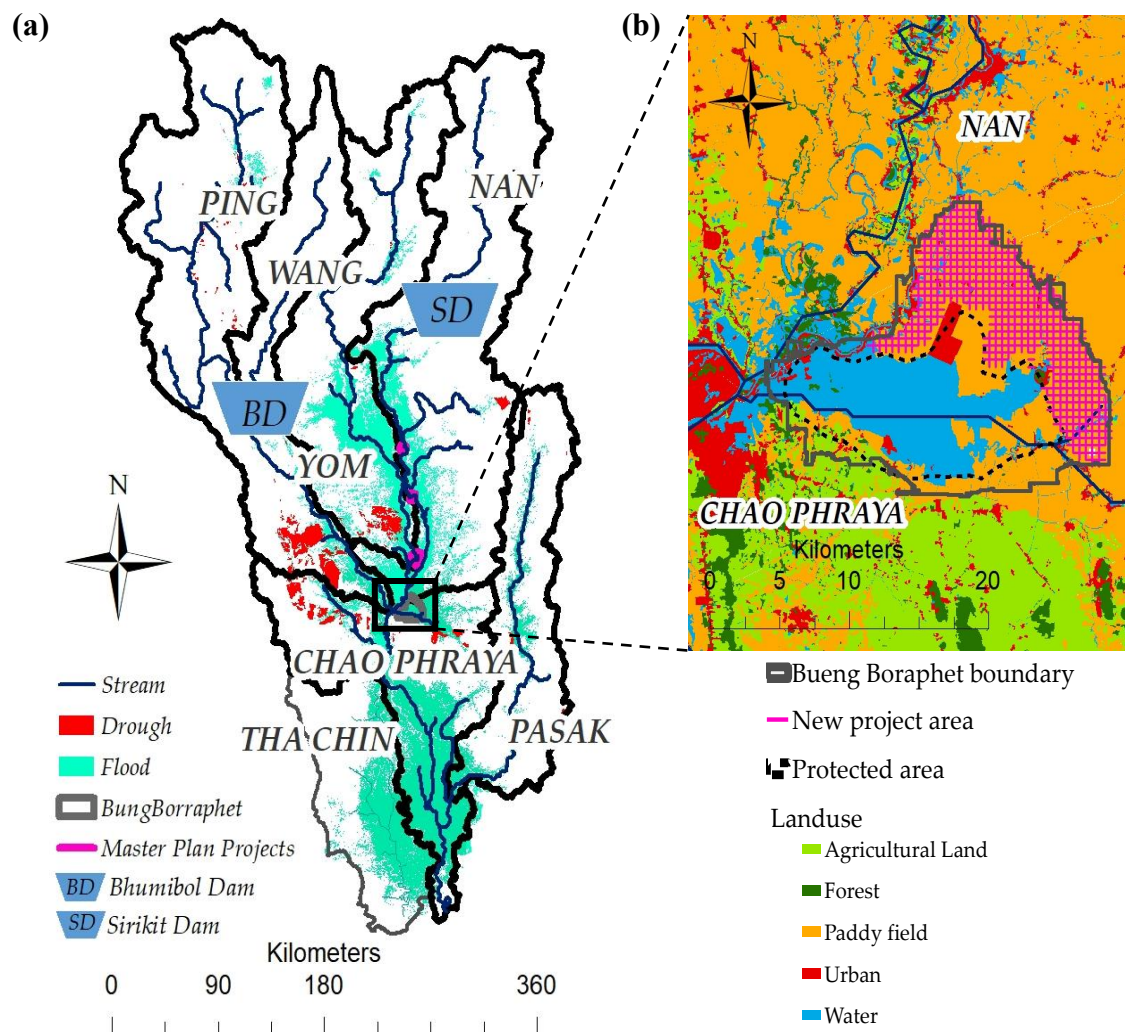


Figure 3.3 Chao Phraya River Basin maps for (a) locations of detention ponds and flood and drought risk areas (b) land use and location of suggested new Monkey's Cheek

Regards to design storage capacity, the available area was deliberated on special law and social conflict. The suitable storage capacity, calculated by the sum-of-end-area method, was suggested to be 685.14 million cubic meters (USDA, 1997). According to the protected zone and village locations, the available areas of 165.80 km² were considered to construct the project represented by pink grid lines in Figure 3.3(b). Concerning above mentions of the new Monkey's Cheek project, the scenario P.4, in Table 3.3, was also investigated regarding the effects on the 2011 flood.

Table 3.3 The explanation for scenarios of detention ponds

Scenario	Explanation
P.0	the retarding basins from Master Plan projects
P.1	the combination of Master Plan projects and scenario S.1
P.2	the combination of Master Plan projects and scenario S.3
P.3	the combination of Master Plan projects and scenario S.8
P.4	the combination of new Monkey's Cheek project and scenario P.3

3.4 Results and Discussion

3.4.1 Calibration and Validation

In order to ensure the model performance, simulated daily river discharge results were compared with observed historical data of 12 gauge stations (Figure 3.2). Calibration (*via* 2008 data) and validation (*via* 2010 data) were performed through three statistical tests, *i.e.*, NSE, RSR, and R². The NSE value range was confirmed to be between 0.51 and 0.83 for the normal hydrological regime as summarized in Table 3.4.

In particular, the examples of the calibrated and validated results at gauge station C.13 are illustrated in Figure 3.4. In Figure 3.4 (b), the overestimation of the model relates to

the abnormal decision of RID to cope with the drought at the beginning of rainy season in 2010 (Vongphet, 2015).

In order to investigate dam operation scenarios, river discharges during the 2011 flood were simulated prior to changing the different water releases from Bhumibol Dam and Sirikit Dam. The simulation of river discharge at station C.2 has the NSE, RSR, and R^2 values being 0.92, 0.28, and 0.94, respectively.

Table 3.4 Calibration and validation results

Station	River Name	Calibration (2008)			Validation (2010)		
		NSE	RSR	R^2	NSE	RSR	R^2
Inflow at Bhumibol Dam	P.1	0.67	0.57	0.64	0.55	0.67	0.74
	Ping River	0.62	0.62	0.72	0.51	0.70	0.57
	P.2A	0.54	0.68	0.55	0.69	0.56	0.65
	Ping River	0.67	0.58	0.55	0.62	0.62	0.64
Inflow at Sirikit Dam	Y.14	0.67	0.58	0.55	0.62	0.62	0.64
	Yom River	0.60	0.63	0.69	0.63	0.61	0.67
	Y.17	0.60	0.63	0.69	0.63	0.61	0.67
	N.64	0.52	0.69	0.67	0.76	0.49	0.74
	Nan River	0.51	0.70	0.71	0.74	0.51	0.75
	N.67	0.72	0.53	0.72	0.83	0.42	0.82
	Nan River	0.59	0.64	0.71	0.66	0.58	0.68
C.2	CPR	0.67	0.57	0.67	0.74	0.51	0.75
C.13	CPR	0.64	0.60	0.70	0.70	0.54	0.74
C.7A	CPR	0.69	0.56	0.71	0.72	0.52	0.70
C.29A	CPR	0.69	0.56	0.71	0.72	0.52	0.70

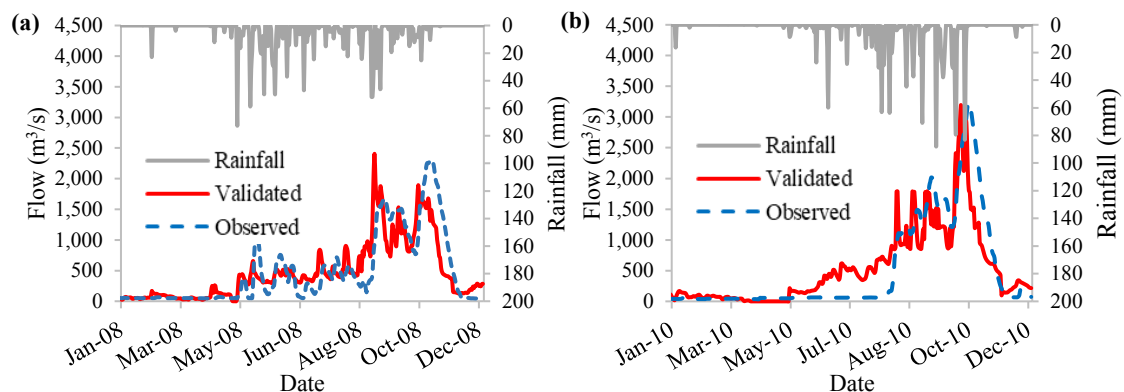


Figure 3.4 (a) Calibration and **(b)** validation of daily river discharges at gauge station C.13, Chao Phraya River

After the calibration and validation, it confirms that the model has well performed in simulating daily river discharges through the normal flow of the year 2008, the drought event in 2010, and the massive floods in 2011. Because the model has been developed in considerations of the CPRB conditions such as dam operation, irrigation projects, land use, *etc.*, these could indicate the usefulness of the model in order to apply extreme rainfall events.

3.4.2 Dam Operation

During the 2011 flood, Bhumibol Dam continuously stored water until it reached its designed capacity (13,510 MCM); only to be forced to discharge at the beginning of October, hence intensified the downstream flood in the Lower CPRB. Within the dam operation scenarios, the maximum dam storage was considered to release the amount of water from Bhumibol and Sirikit Dams in the different timing. The simulated river discharge results at gauge station C.2 are depicted in Figure 3.5.

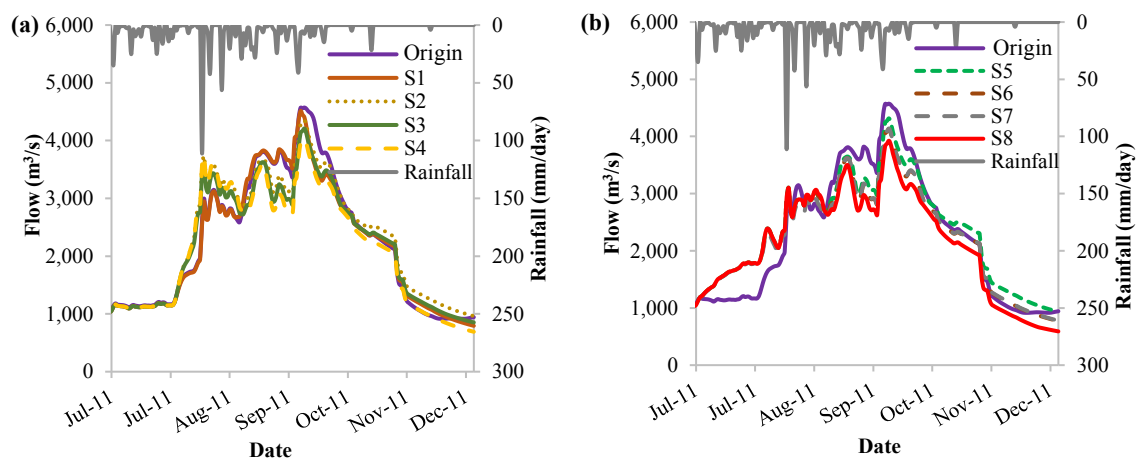


Figure 3.5 Simulated flows at gauge station C.2 with setting release storage ratios of (a) scenarios S.1-S.4 and (b) scenarios S.5-S.8

In scenario S.1 in Figure 3.5(a), the minor reduction of water releases due to the reservoir limit at the beginning of October marginally attenuated the highest flow peak to 4,512 m³/s at gauge station C.2. By increasing the water release in August and decreasing it in October from both upstream dams in scenarios S.2-S.4, the highest flow peak of scenario S.4 was cut to 4,038 m³/s, yet the overflow occurs in the middle of August. Scenario S.3 resulted in a reduction to 4,208 m³/s of highest flow peak and 74 percent of overflow reduction during the flood. Scenario S.3, as such, would provide the most appropriate release storage ratio for both dams to mitigate flood impacts in the downstream side of CPRB.

As shown in Figure 3.5(b), scenarios S.5-S.8 discharge a higher amount of water starting from July to prepare additional storage capacity during the flood. The results have highlighted that a 90 percent of overflow volume and 3,924 m³/s of highest flow peak are reduced in scenario S.8 in Figure 3.5(b) and Figure 3.6. This scenario resembles the actual dam operation during the 2011 flood. Notwithstanding, all eight scenarios result in peak flows that are greater than the maximum river capacity even if the dams release a smaller amount of water during the flood of 2011. Apart from the ineffective operation of upstream dams, the abnormal rainfall also contributed significantly to the flood extent in 2011 (Aon, 2012; Bidorn *et al.*, 2015; Komori *et al.*, 2012).

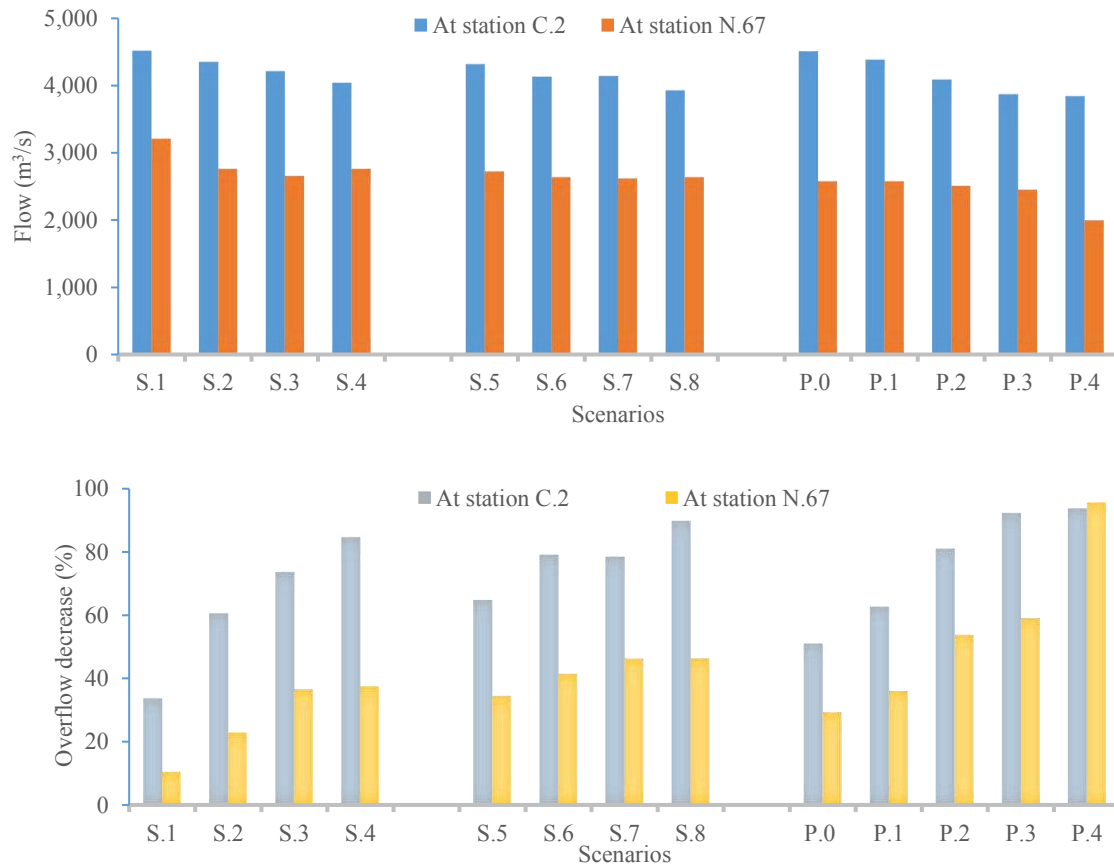


Figure 3.6 Summaries for scenario results of **(a)** maximum flow rate and **(b)** overflow decrease percentage at gauge stations C.2 and N.67

To ensure an appropriate dam operation (scenario S.8), the approach used was to examine the impacts on river discharges at the CPR origin under different hydrological regimes, including the flood situation of the year 2006, the normal hydrological regimes during 2007-2010 period, and the drought event of the year 2012 as shown in Figure 3.7. In order to realize the simulated flow for the flood condition, it has to be noticed that flow rates rise before the flood occurrence during July-August period because of increasing water releases from the dams; thenceforth, the highest flow peak of the flood can be attenuated to $5,256 \text{ m}^3/\text{s}$, which is an overflow volume decrease of 22 percent. Noticeably, the flow peaks of the year 2006 exceed the peaks of the year 2011 due to the high rainfall

intensity at the middle part of CPRB; however, the 2006 flood did not spread over CPRB as the 2011 flood (Promchote *et al.*, 2016).

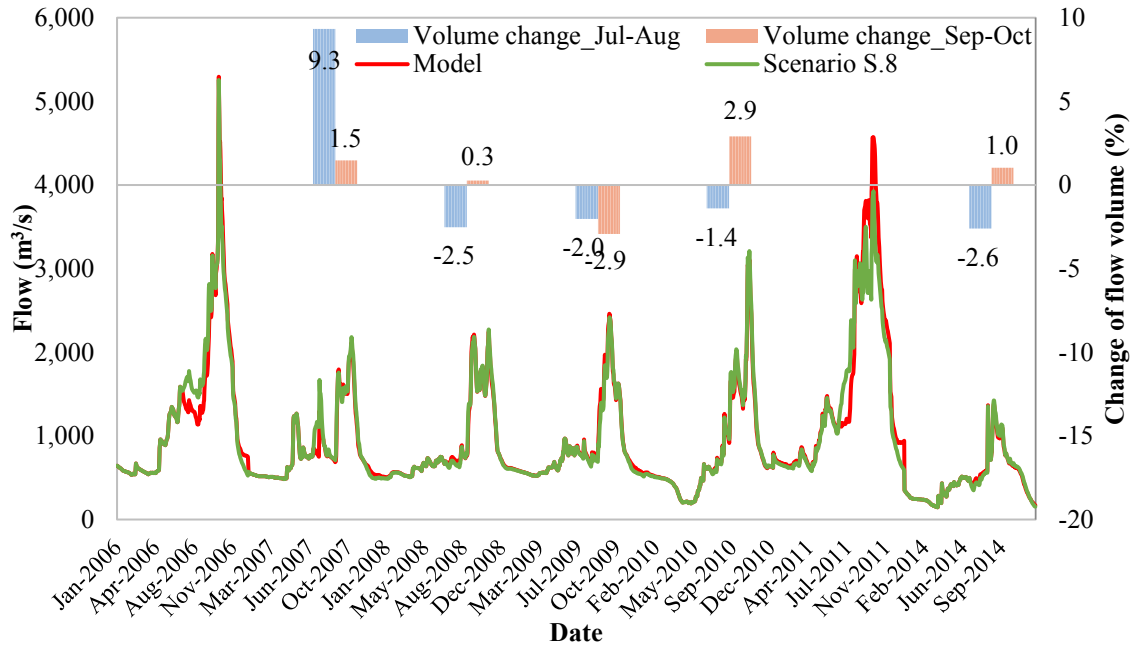


Figure 3.7 Simulated flows at gauge station C.2 with scenarios S.8 for flood situation of the year 2006, the normal hydrological regime of the period 2007-2010, and drought situation of the year 2014

The simulated flows of the normal hydrological regime shows that the flows at gauge station C.2 are elevated about 1-9 percent in 2007. It means that the scenario S.8 releases more water from the dams since the dams have higher water levels after the flood in 2006. As a consequence, the river discharges are flattened out by approximately 1-3 percent during the rainy season of the years 2008-2010 (Figure 3.7). At the end of the rainy season of the year 2010, the discharges, however, increase by 3 percent due to the high rainfall intensity. For that reason, the scenario S.8 releases a bigger water volume, so that the dams could have more storage capacity for flood control. In consideration of the drought in 2014, it's important to underline that a comparison between simulations with and

without the scenario S.8 are creating slight changes on the flows. From these results, effective dam operations are key to control downstream river discharges during floods and droughts.

3.4.3 Detention Ponds (Monkey's Cheek Projects)

With regards to the question how the performance of the retarding basins and retention ponds proposed by Thai Master Plan can mitigate future floods, the approach was examined under the 2011 flood by the scenarios P.0-P.3, shown in Figure 3.7. Without dam operation scenarios, the scenario P.0 has resulted in a reduced river discharge of 51 percent and overflow reduction of 29 percent at the CPR origin (Station C.2) and the downstream of Nan River (Station N.67), respectively. In scenario P.3, including scenario S.8, the overflow volume is decreased to 59 percent at the downstream of Nan River. It should be underlined that the proposed projects by the Thai Master Plan are not so effective in mitigating the flood (Jamrussri and Toda, 2017).

The scenario P.4 was developed from scenario P.3 with the integration of the new Monkey's Cheek project. As a result, the overflow volumes are flattened out by 94 percent at the gauge station C.2; in particular, the new project could attenuate additionally 37 percent of the volume at the gauge station N.67.

The results of the former approaches could not satisfy for flood prevention. It's important to develop additional plans to prevent future extreme floods. Due to the CPRB's topography, numerous natural and constructed ponds are located in the basin. No discipline rules and guidelines, however, govern how the ponds should operate for flood and drought mitigations. These should be taken into account for additional approaches during integrated watershed management. Considering the concept of the integrated flood

management, it must be interdependent and not only include water resource management but also aspects of the environment, society, government, and economy (Groblicki *et al.*, 2015). Pond management is a rational suggestion of both structural and non-structural measures in the watershed management plan for future flood and drought preventions. The pond management is simultaneously investigated and explained in Chapter 5.

3.5 Summary

The hydrological model was efficiently established using HSPF within the first exploration of parameter value ranges for the CPRB. In order to ensure the model performance, the 12 gauge stations represent the NSE values range between 0.51 and 0.83 for calibration (*via* 2008) and validation (*via* 2010). Regarding the flood in 2011, the inundation could not be prevented even if the dams released a small amount of water. For an appropriate dam operation to deal with future floods, it is suggested to discharge a higher amount of water starting from July. It damps out 90 percent of the overflow volume with 3,924 m³/s as the highest flow peak at the CPR origin. A part of the approach is the impacts on the other hydrological regimes. The archived results emphasize that the flows create insignificant changes during the normal hydrological regime and drought event.

Detention ponds are proposed in the view of the retarding basins by the Thai Master Plan and the suggested new Monkey's Cheek. The simulation results of the retarding basins, however, have found that these projects could not effectively mitigate the 2011 flood. Accordingly, a new Monkey's Cheek project is suggested to mitigate floods at the downstream of Nan River. The combination of considerable dam operation, retarding basin and Monkey's Cheek project could flatten out 94 percent of overflow volumes at the CPR origin and 96 percent at downstream of Nan River.

Regarding the suggested approaches by this Chapter, the simulated results of a combination of structural and non-structural measures could mitigate the flood, but could not prevent overflows. In order to avoid floods in the future, understanding trend of future climate change is important as described in Chapter 4. An additional management, such as pond management, and dam operations are also explained in Chapters 5 and 6, respectively.

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Chapter 4

Post-Processing d4PDF Data for Applying Local Conditions

4.1 Introduction

In order to prevent damage against future severe floods and droughts, it is important to plan at the same time as performing integrated watershed management, effective dam operations, drainage management, operations of irrigation systems, and so on. Prediction of climate change can identify the possibilities for disaster occurrences. Numerous climate change models have been developing with differences in initial conditions, internal and external forces, *etc.* Focusing on the Chao Phraya River Basin (CPRB), a number of climate change models such as the Asian Precipitation–Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE), the Tropical Rainfall Measuring Mission (TRMM), the general circulation model (GCM), the Commonwealth Scientific and Industrial Research Organisation (CSIRO), the Japan Meteorological Research Institute (MRI) of atmospheric general circulation model (AGCM), and the third and fifth phases of the Coupled Model Inter-comparison Project (CMIP3 and CMIP5) have been simulated using hydrological models for CPRB (Kure and Tebakari, 2012; Ogata *et al.*, 2012; Ligaray *et al.*, 2015; Supharatid, 2015; Promchote *et al.*, 2016). However, how can decision-makers select which climate change model is suited to predict extreme events? As considered the pros and cons of those models in

Chapter 2, the database for Policy Decision making for future climate change (d4PDF) model has improved uncertainties from other models and provided sporadic occurrences in precipitation. More specifically, the d4PDF model has not been applied to the local conditions and simulated in the hydrological model of the CPRB. For the reasons given, we have considered using the d4PDF model. This chapter aims to develop post-processing techniques using the d4PDF model based on climate pattern and local conditions of the CPRB. The second objective is to explore trends of the post-processing d4PDF outputs, including rainfall and temperature.

4.2 Methodology

Interpolation and bias correction methods are key post-processing techniques for addressing global climate data under local conditions. In addition, some approaches need to be added to the accomplishment of the two methods as shown in Figure 4.1.

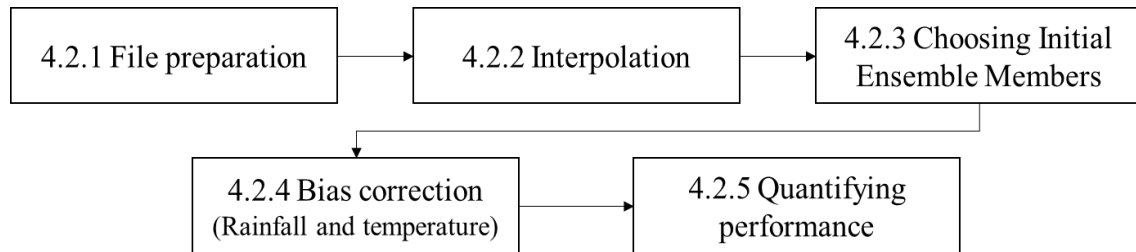


Figure 4.1 Flowchart of methodology

4.2.1 d4PDF Datasets

4.2.1.1 d4PDF Information

The d4PDF model was applied from the outputs of a global atmospheric model with a horizontal grid spacing of 60 km of version 3.2 (AGCM3.2). A historical climate data, provided 100 ensemble members from 1951 to 2010, was simulated by setting the lower

boundary conditions for observed monthly mean sea surface temperature (SST), sea ice concentration (SIC), and climatological monthly sea ice thickness (SIT). Regarding to the future climate from 2051 to 2110, using +4K simulation, the climatological sea surface temperature (SST) warming patterns of six CMIP5 models, in which covered main uncertainties from the models, were used in the future d4PDF dataset. The six SST warming patterns were multiplied different scaling factors. Additionally, each ensemble has 15 members with used different initial conditions and sea surface temperature (SST) perturbations; CCSM4 (CC), GFDL-CM3 (GF), Had-GEM-AO (HA), MIROC5 (MI), MPI-ESM-MR (MP), and MRI-CGCM3 (MR). In the scope of this chapter, we considered reducing the number of ensembles due to the previous findings of the differences in the probability distribution function of maximum river discharges at the Indochinese Peninsula including the CPRB (Hanittinan and Ichikawa, 2017). They found that MI, MP and MR ensembles had a significant difference in the prior probability distribution at CPRB. Therefore, these three ensembles (MI, MP and MR) are input and used in this research.

4.2.1.2 File Preparation

The database for Policy Decision making for Future climate change (d4PDF) has been downloaded from Data Integration and Analysis System Program (DIAS) (<http://d4pdf.diasjp.net/d4PDF.cgi?target=GCM&amp;amp;amp;amp;amp;am p;amp;amp;amp;amp;amp;lang=en>). The d4PDF data are stored in the .dat format file, which contains a large gridded data in the form of the binary file. To input the data into the hydrological model and the water budget model, the binary files have been converted into the .mat format that provides time-series data using MATLAB software.

4.2.2 Interpolation

The d4PDF data consists of the gridded cells with the horizontal 60-km resolution; however, the observed data are specified and recorded at the met gauge stations provided by the Thai Meteorological Department (TMD). Due to the different positions between d4PDF gridded cells and met gauge stations, the interpolation method is required to match two datasets at the similar locations where the observed data at met gauge stations are interpolated into the gridded cells. The distances, latitudes, and longitudes between the met gauge stations and also the topography of CPR basin, which the elevation is about 0-2,500 meters above mean sea level have been taken into account in the use of an effective interpolation method. As far as the limitation is concerned, 22 met gauge stations are available over 150,000 km² in the CPRB region. Due to the number of met gauge stations, the deterministic method, assuming to be continuous surface, was chosen instead of the probabilistic method (Nalder and Wein, 1998). However, the elevations are not applicable to the deterministic method. In order to resolve this lack, Gradient-plus-Inverse-Distance-Squared (GIDS), combined procedure between multiple linear regression and distance weighting, was considered to apply using Equation 4.1 (Stahl *et al.*, 2006).

$$X_p = \left[\sum_{i=1}^n \left(\frac{1}{d_i} \right)^2 \right]^{-1} \times \sum_{i=1}^n \left\{ \left[X_i + b_1(Long_p - Long_i) + b_2(Lat_p - Lat_i) + b_3(h_p - h_i) \times \left(\frac{1}{d_i} \right)^2 \right] \right\} \quad (4.1)$$

In Equation 4.1, *Long* and *Lat* are the coordinates of longitude and latitude, respectively, *h* is the elevation, and *b*₁, *b*₂, *b*₃ are the regression coefficients for *Long*, *Lat*, and *h*, respectively. The *d* is the distance from the observed site to the gridded cell site. *X*_{*i*} and *X*_{*p*} are rainfall/temperature at the observed site '*i*' and the gridded cell site '*p*', respectively.

4.2.3 Initial Ensemble Members

Hundred ensemble members for historical simulated data are provided in the d4PDF database; however, only a few ensemble members that match with the observed data need to do bias correction and input in the models. A step in choosing initial ensemble members leads to decrease the computer running time. Interpolated rainfall data from observed data at each gridded cell are compared to the original d4PDF data of 100 members at 68 gridded cells. Then, three statistical tests (Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and correlation coefficient (R)) of rainfall data have resulted in order to select appropriate ensemble members. These statistical values at each gridded cell were counted one score when the value is higher than 90th percentile as the results shown in Figure 4.2. As a result, eight ensemble members (m006, m008, m019, m022, m025, m30, m062, and m096) were chosen to apply the bias correction

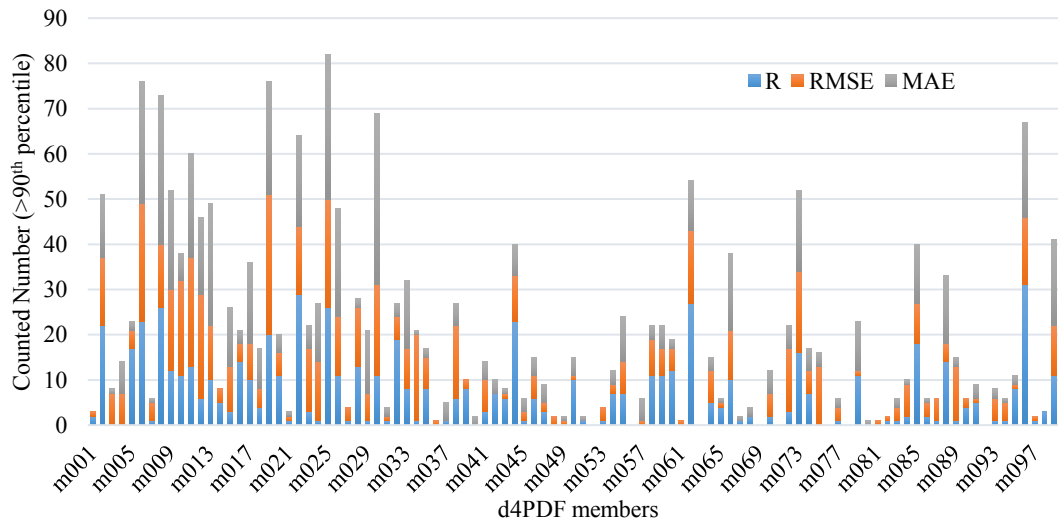


Figure 4.2 Counted numbers of hundred members of historical d4PDF data calculated by 90th percentiles of statistical tests (RMSE, MAE and R)

4.2.4 Bias Correction

4.2.4.1 Rainfall

Due to the large differences in rainfall values between historical d4PDF data and observed data from the step of choosing initial ensemble members, the post-process using bias correction is required to fit data uncertainty for the CPRB. Mainly five bias correction methods, which are linear scaling, elevation bias correction, power transformation, distribution transformation, and quantile mapping are trendy applied corrected standard deviation or percentiles for simulated precipitation. Each method has different advantages and disadvantages due to the setting of assumptions and parameters. In the scope of this research, daily d4PDF rainfall data were needed to adjust statistical distribution closed to the observed rainfall. Gumindoga *et al.* (2016) indicated that the quantile mapping approaches are the most effective production for daily rainfall data. Quantile mapping approach mainly consists of several methods, such as an Empirical cumulative distribution function (Non-parametric transformation) and Gamma distribution (Distribution derived transformation). However, these statistical transformation methods have the limitation that the future climate data are typically applied by similar corrections from observed values. In view of that, the future values could not be assessed if the variables exceed the range of observed values (Gudmundsson *et al.*, 2012). As the distribution derived transformation assessed a Gamma distribution method, the similar restriction of the transformation approach is not appropriate for extreme rainfall values. In order to overcome this limitation, a gamma distribution combined with a Generalized Pareto Distribution (Gamma & GPD) was applied for bias correction of daily rainfall time-series (Yang *et al.*, 2010; Gutjahr and Heinemann, 2013).

A. Equations and Approaches

The Gamma & GPD method could improve the future rainfall values as referred to an actual climatology from observed data. Particularly, the Gamma distribution assesses the values below the 95th percentile of rainfall distribution (Piani *et al.*, 2010). Moreover, the Generalized Pareto Distribution implies tailed distribution as extreme values which are above the 95th percentile of the distribution as in Equation 4.2 (Coles, 2001; Gutjahr and Heinemann, 2013)

$$y = \begin{cases} F_{obs, gamma}^{-1}(F_{Model, gamma}), & x < 95th \text{ percentile} \\ F_{obs, GPD}^{-1}(F_{Model, GPD}), & x \geq 95th \text{ percentile} \end{cases} \quad (4.2)$$

In Equation 4.2, $F_{Model, gamma}$ is a gamma function computed by the model data, $F_{obs, gamma}^{-1}$ is the inversed gamma function using observations as the function defined from Equations 4.3 and 4.4. $F_{Model, GPD}$ is a Generalized Pareto Distribution (GPD) function; and, $F_{obs, GPD}^{-1}$ is the inversed function. Then, the GDP function is assessed by Equation 4.5;

$$f(x) = \frac{\left(\frac{x}{\beta}\right)^{\alpha-1}}{\beta \Gamma(\alpha)} \exp\left(-\frac{x}{\beta}\right), \quad x, \alpha, \beta > 0 \quad (4.3)$$

In Equation 4.3, x is normalized daily rainfall; and, x should be $x > \varepsilon > 0$, which ε is a fit of simulated and observed rainfall distributions. $\Gamma(x)$ is a gamma function; and, scale (β) and shape (α) parameters are estimated by method of Maximum Likelihood as in Equation 4.4 (Wilks, 2006). More specifically, D is calculated by the natural log of the mean value ($\bar{x}$) and the mean of logs of rainfall data (x_i) in Equation 4.4a.

$$D = \ln(\bar{x}) - \frac{1}{n} \sum_{i=1}^n \ln(x_i) \quad (4.4a)$$

$$\alpha = \frac{1 + \sqrt{1 + 4D/3}}{4D} \quad (4.4b)$$

$$\beta = \frac{\bar{x}}{\alpha} \quad (4.4c)$$

The Generalized Pareto Distribution (GPD) implies a tailed extreme when the value is above 95th percentile (Coles, 2001), defined as follows:

$$\Pr(X - u \leq x | X > u) = \begin{cases} 1 - \left(1 + \frac{\xi x}{\tilde{\sigma}}\right)^{\frac{-1}{\xi}}, & \text{if } \xi \neq 0 \\ 1 - \exp\left(-\frac{x}{\tilde{\sigma}}\right), & \text{if } \xi = 0 \end{cases} \quad (4.5)$$

In Equation 4.5, as u is the threshold value at 95th percentile which is a different value between observed and simulated data, X is the subset of daily rainfall above 95th percentile. A shape parameter (ξ) for GPD is estimated by Equation 4.4b, and the scale parameter ($\tilde{\sigma}$) is calculated by $\tilde{\sigma} = \sigma + \xi(u - \bar{x})$.

B. Model Setup

Due to the different patterns of rainfall by time-to-time, time windows that affect parameter values in Equation 4.4 are considered by seasonality and month in this chapter. Thus, the daily rainfall time-series were separated into rainy and dry seasonal datasets. Regarding the seasonal time window, since extreme rainfall is not concerned during the dry season, the dry seasonal dataset is processed by the gamma distribution (Gamma) approach. On the other hand, the gamma distribution combined with a Generalized Pareto Distribution (Gamma & GPD) applies to the rainy seasonal datasets as extreme rainfall values play a significant role in predicting future floods during the rainy season. Daily rainfall time-series were also prepared into monthly datasets while considering the monthly time window. Monthly datasets between November and April were proceeded

by the Gamma approach for the dry season, and the datasets between May and October were processed using the Gamma & GPD method for the rainy season. Both time windows in each dataset were set to calculate scale (β) and shape (α) parameters in the Maximum Likelihood method in Equation 4.4. The Gamma or Gamma & GPD approaches then proceed to reduce the d4PDF biases.

Through considering time windows, the Gamma and the Gamma & GPD methods decrease the biases of the raw historical d4PDF data (the years 2000-2010) of eight members (in Section 4.2.3). Only one member was chosen by good performance. Then, the parameters of the greatest performance member were applied for future d4PDF data of three ensembles (MI, MP and MR) that each comprises 15 ensemble members. For this research, daily rainfall data were prepared for two periods: 2051-2070 and 2091-2110. Future rainfall time-series have been replicated through the developed bias correction approaches to predict future daily rainfalls. Due to the large simulated data, the results are presented for minimum and maximum of annual rainfall values.

4.2.4.2 Temperature

Since the observed and d4PDF temperature data are of high variability, an appropriate bias correction method is required to reduce the variabilities. However, the temperature pattern is normally different from the rainfall pattern; therefore, the methods of bias correction (*e.g.*, Gamma and Gamma & GPD) used to precipitation could not be applied to the temperature. Within the reference and the concept of bias correction for temperature in Chapter 2, the quantile mapping approach is generally assessed. The three statistical transforms were considered as assumptions in this research. Firstly, a cumulative distribution function matching (CDFm) method assumes that only historical modelled

temperature distribution applies to the future distribution (Li *et al.*, 2010; Pierce *et al.*, 2015). Secondly, a cumulative distribution function transform (CDF-t) approach defines that the difference between historical observed and modelled distributions is assessed to the future distribution (Michelangeli *et al.*, 2009; Guo *et al.*, 2018). Finally, the assumption of an equidistant cumulative distribution function matching (EDCDFm) method using the relationship between observed and modelled distributions during the historical period is established for the future distribution, considering both future and historical time periods (Li *et al.*, 2010). Due to the comprehensiveness of the EDCDFm method, maximum and minimum temperatures were applied as in Equation 4.6.

$$X_{Gf,adjust} = X_{Gf} + F_{Sh}^{-1} \left(F_{Gf}(X_{Gf}) \right) - F_{Gh}^{-1} \left(F_{Gf}(X_{Gf}) \right) \quad (4.6)$$

In Equation 4.6, F is the cumulative distribution function (CDF) as Sh represents for historical observation, Gh for historical models; and, Gf is the future models. F^{-1} defines the inversed CDF and X_{Gf} denotes the maximum or minimum temperature at the future time period.

4.2.5 Quantifying Performance

4.2.5.1 Performance Assessment

In general, statistical tests assess the performance assessment of the model. Mean absolute error (MAE), root mean square error (RMSE), mean bias, Pearson's product-moment correlation coefficient, and correlation coefficient (r) commonly evaluate performance (Piani *et al.*, 2010; Evans *et al.*, 2012; Yang *et al.*, 2015). The performance assessment of this chapter is also evaluated by MAE and RMSE, as in Equations 4.7 and 4.8.

$$MAE = \frac{\sum_{i=1}^n (Z_i - Z'_i)}{n} \quad (4.7)$$

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(Z_i - Z'_i)^2}{n}} \quad (4.8)$$

In Equations 4.7 and 4.8, Z_i is an observed rainfall; Z'_i is a model rainfall at a time (i); and, n is the number of total days. MAE and RMSE have lower values that define smaller errors between observed and model data.

4.2.5.2 Skill Scores

However, statistical tests (MAE, RMSE, *etc.*) have a limitation to identify into an overall measure. For example, the RMSE gives emphasis to high errors while the MAE is less sensitive to extreme values (Hofstra *et al.*, 2008). In order to achieve a global comparison of the different statistical methods, Evans *et al.* (2012) have suggested the relationship of the mean absolute error (MAE) between the observed and corrected rainfall data to determine a global evaluation. The skill scores assess MAE values of ten intervals of the observed CDF (MAE0.1, MAE0.2, ..., and MAE1.0). The global evaluation is computed by mean of the ten intervals (Evans *et al.*, 2012; Gutjahr and Heinemann, 2013). The mean MAE value for each grid cell was calculated for the determination of an appropriate ensemble of historical data from eight ensemble members (m006, m008, m019, m022, m025, m30, m062, and m096). As the lowest value of the mean MAE, a suitable ensemble was chosen to apply the bias correction for future daily rainfall.

4.3 Results and Discussion

4.3.1 Bias Correction for Rainfall

4.3.1.1 Performance

The method of bias correction is applied in considerations of the rainfall pattern and other conditions of the CPRB. Due to these criteria, a gamma distribution (Gamma) method corrects daily rainfall data of dry seasons. Additionally, the gamma distribution combined with a Generalized Pareto Distribution (Gamma & GPD) approach reduces the biases of rainy seasonal datasets. Seasonal and monthly time windows are taken into account in the calculation of parameters in the two methods. Best performance is also discussed for use and application with future predictions.

A. Comparisons of Seasonal and Monthly Time Windows

As regards the comparison between seasonal and monthly time windows on dry seasonal datasets, it is noted that the number of dry days by setting the monthly time window is generally higher than by using the seasonal time window. For example, the number of days with no rainfall using the monthly time window is approximately 4.5% higher at a grid cell located in the Lower CPRB as shown in Figure 4.3(a). Specifically, the cumulative distribution function (CDF) values of the dry days, Figure 4.3(b), are 0.50 and 0.55 through seasonal and monthly time windows, respectively. Particularly, the monthly time window could increase the CDF value by about 0.02 from the original d4PDF and 0.20 from the observation. The increase or decrease in days with no rainfall depends on the time window in the calculation of mean value, while the transfer function is not related (Piani *et al.*, 2010). Consequently, a gamma distribution with setting

monthly time window of dry season dataset could increase the number of dry days. This approach could subsequently predict more frequency and consecutive period of future drought events.

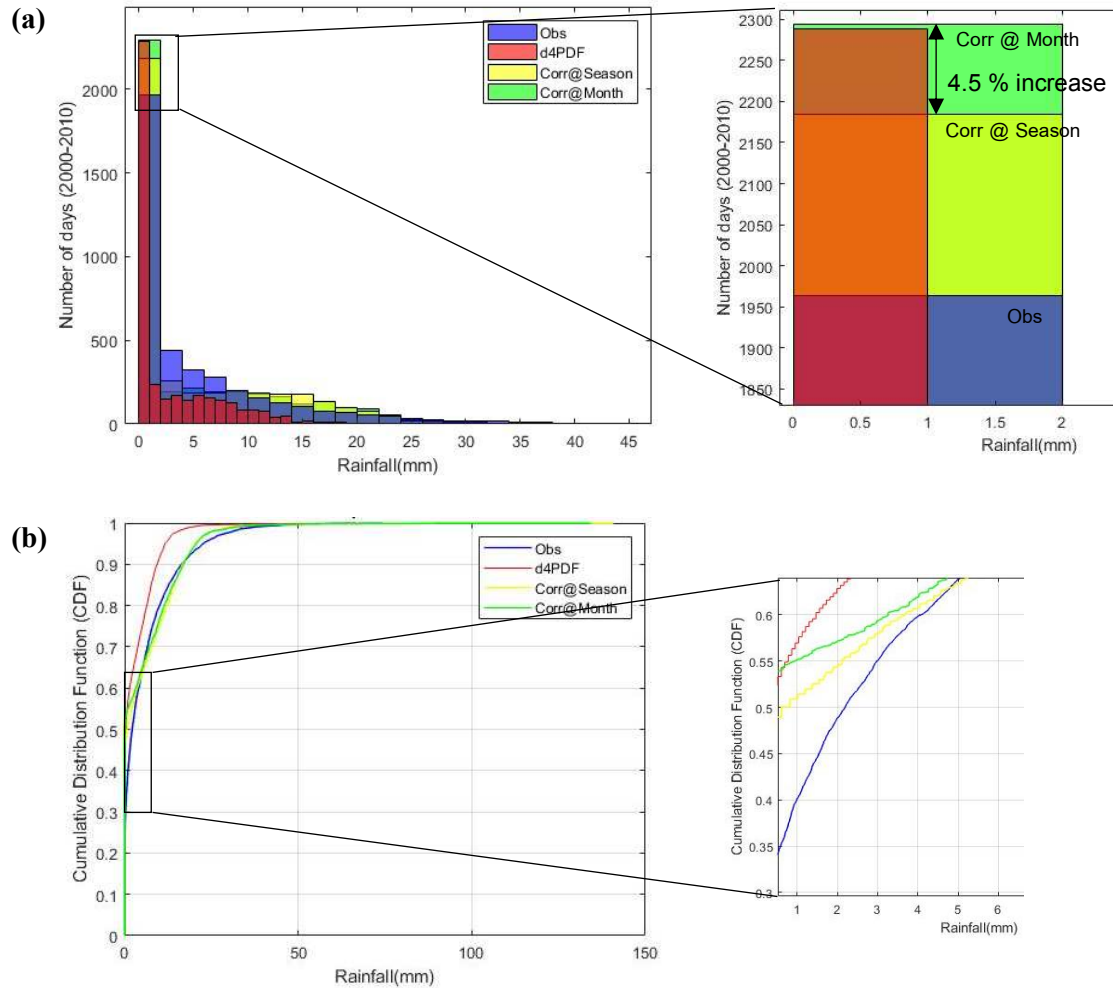


Figure 4.3 (a) Histogram and (b) cumulative distribution function (CDF) of the ensemble member m030 at grid cell located in the Lower CPRB

Given the purpose of extreme flood prediction, the gamma distribution combined with a Generalized Pareto Distribution (Gamma & GPD) approach was proceeded by rainy seasonal datasets. After bias correction, the 95th percentile value of corrected rainfall is higher than the observation's value (Figure 4.3(b)). Also, rainfall amount at 99th percentile *via* setting seasonal time window is greater than *via* monthly time window

because the means and standard deviation of the seasonal time window as parameters are mostly higher or equal to the monthly time window. Due to the increasing values, the two parameters (ξ , $\tilde{\sigma}$) defined in Equation 4.5 have the better fitting of the extreme value from 99.6 mm of d4PDF output to 140.8 mm/day. In order to predict extreme future rainfall, the seasonal time window is chosen to use in the Gamma & GPD approach for rainy seasonal datasets.

As far as the skill scores are concerned, the MAE values between 30th and 80th percentiles of corrected outputs are higher than the d4PDF data, as shown in Figure 4.4. In the event of heavy rainfall, the MAE1.0 value of corrected outputs, calculated from 90th to 100th percentiles, is smaller than the value of d4PDF because lower than 95th percentile rainfall was applied by Gamma method while above 95th percentile was fitted *via* the GDP approach. It could imply that the bias correction will enhance most of the ranges of rainfall amounts.

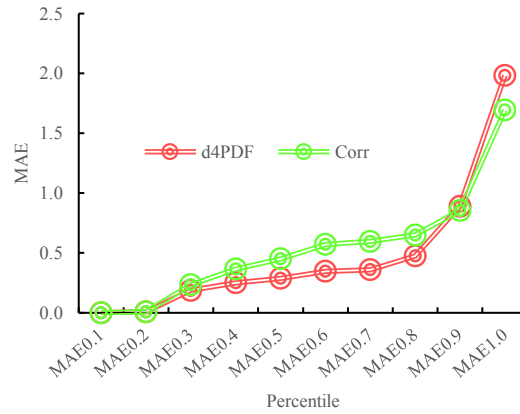


Figure 4.4 MAE values at each interval of CDF

B. Greatest Performance

In order to apply the bias correction for future data, only an ensemble of historical d4PDF output is needed due to the definition of statistical transformations, with the aim of adjusting the similar distribution from historical observation and model data to the future model data. Figure 4.5 shows the comparison of the MAE means of eight d4PDF members *via* the skill score method.

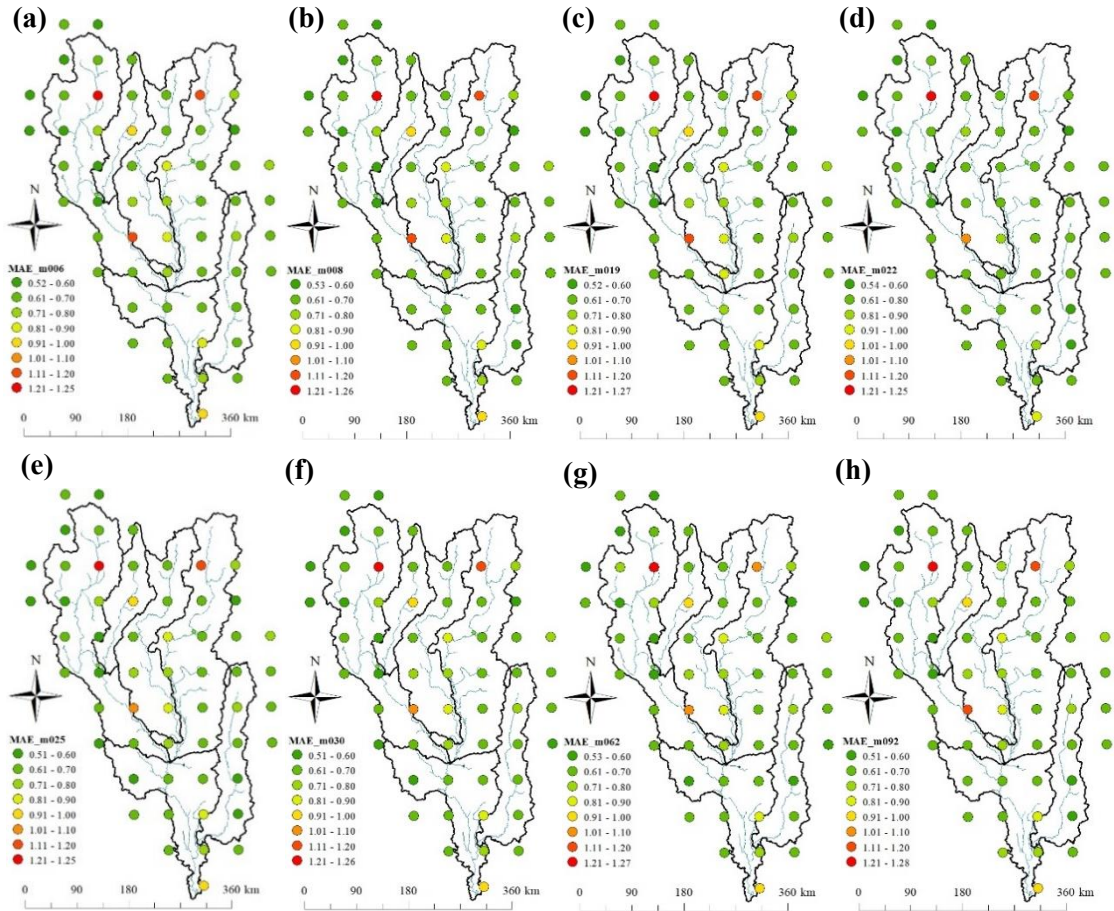


Figure 4.5 The mean MAE, computed by skill scores method, of historical d4PDF members (a) m006, (b) m008, (c) m019, (d) m022, (e) m025, (f) m030, (g) m062, and (h) m092

The lower MAE means (green dots) have a smaller error in the difference between observation and model. From Figure 4.5, the members m025, m030, and m062 have lower

MAE means than others. Considering the different annual rainfall means calculated from 2000 to 2010 in Figure 4.6, it is found that the member m030 has the smallest biases of annual means. The parameters of the member m030 are suitable to apply bias correction for future rainfall.

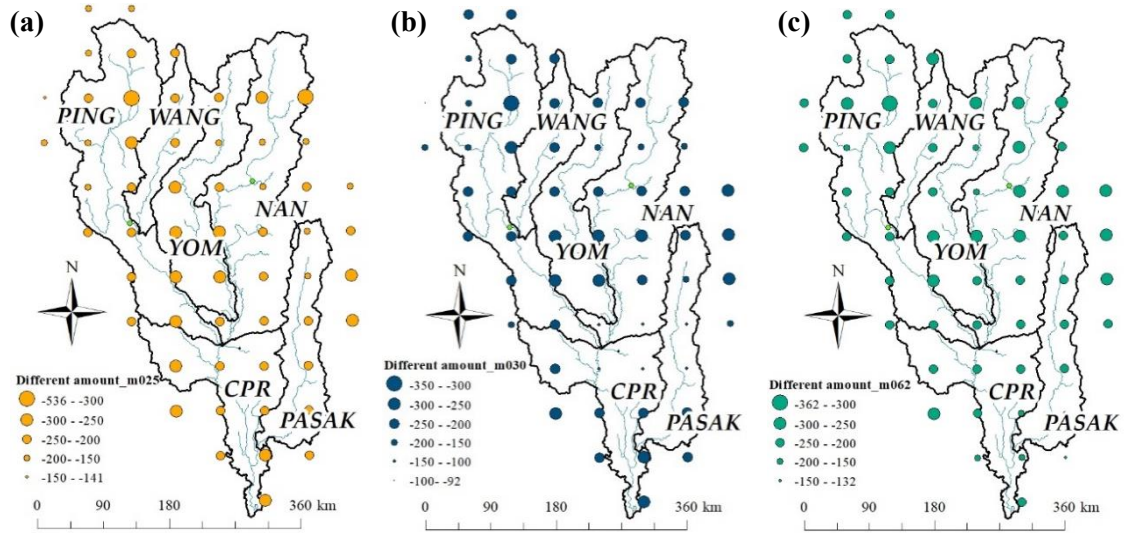


Figure 4.6 The differences of average annual rainfall values of the years 2000-2010 between observation and correction through members (a) m025, (b) m030, and (c) m062

4.3.1.2 Trends of Corrected Output

A. Historical Data

After the bias correction, the increasing rainfall means of the rainy seasonal dataset at all stations are heightened through the Gamma & GPD approach with the seasonal time window, as shown in Figure 4.7. A generalized Pareto distribution could be calculated the tail rainfall values above 95th percentile. Also, the seasonal time window could increase the means, standard deviations, and 95th percentile values. Comparing the accumulated rainy seasonal rainfall between observed and corrected data, the values for most gridded cells tend to be similar (Figures 4.7a and 4.7b). In particular, the accumulated rainfall during the 2000-2010 rainy season is approximately 1,000-1,730

mm per year. Markedly, the corrected outputs are slightly underestimated, indicating less than 200 mm at the middle part of the Upper CPRB and downstream of the Lower CPRB. In contrast, the raw d4PDF data are almost lower than both observations and corrections at most of the gridded cells, excepting the north of the CPRB (Figure 4.7c).

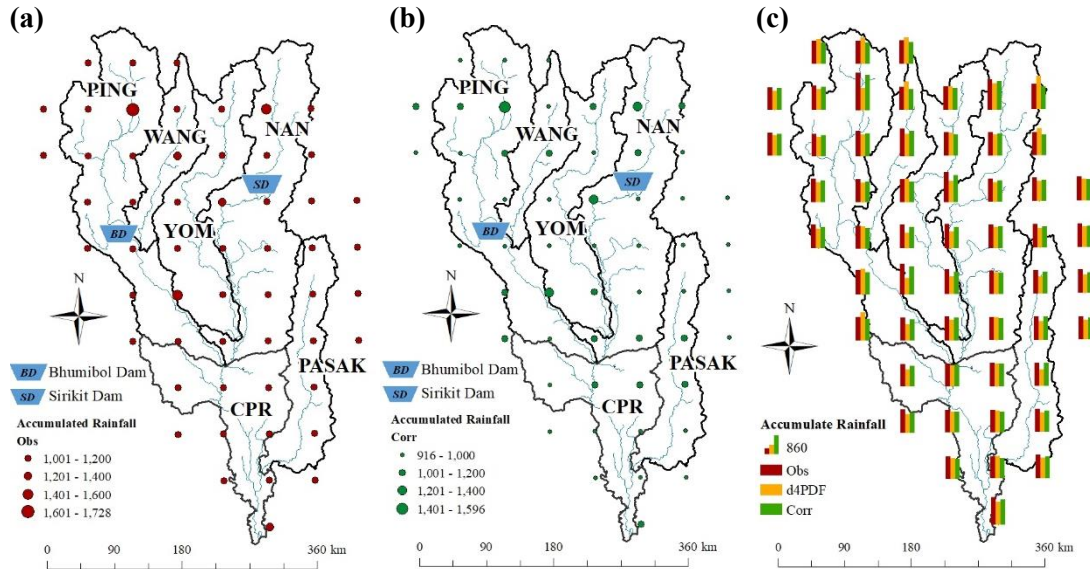


Figure 4.7 Average accumulated rainfall values of rainy seasons of the years 2000-2010 for (a) observed data, (b) corrected data, and (c) the accumulated rainfall means of daily rainfall for observed, raw d4PDF and corrected data

As far as the dry seasonal dataset is concerned, the gamma distribution method has been applied by setting monthly time window. Monthly separation helps to increase days with no rainfall and to decrease the means; the water crisis may, therefore, be predicted in the future. Figure 4.8 shows the increasing means of correction from the raw d4PDF data; however, the means at most gridded cells are underestimated in comparison to observation. Accumulated rainfall means for the period 2000-2010 are 170-280 mm/year of observation and 120-220 mm/year of correction.

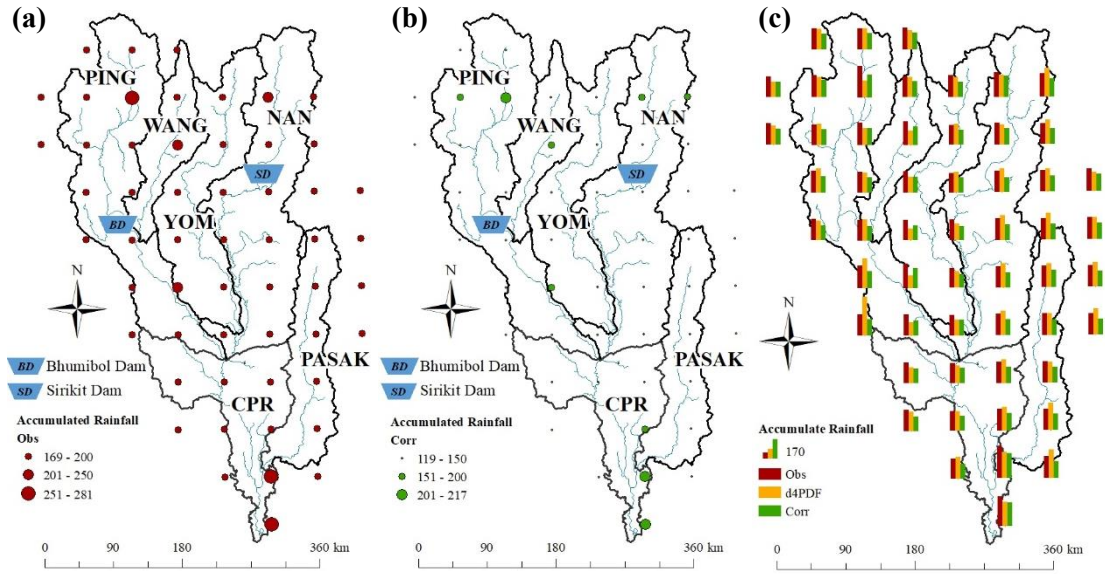


Figure 4.8 Average accumulated rainfall values of dry seasons of the years 2000-2010 for (a) observed data, (b) corrected data, and (c) the accumulated rainfall means of daily rainfall for observed, raw d4PDF and corrected data

In general, the accumulated rainfall values at the north past of Ping and Nan River Basins have significant variance between raw d4PDF data and observation, in which the raw d4PDF data are widely undervalued at most gridded cells, during the years 2000-2010 (Figures 4.7 and 4.8). Due to the difference, even corrected data are improved *via* bias correction, especially in the north past of Ping and Nan River Basins, which is still underestimated.

B. Future Data

The reduction of the d4PDF biases is carried out *via* the Gamma method using the monthly time window for dry season datasets and the Gamma & GPD method setting seasonal time window for rainy season datasets. The developed bias correction methods then have performed three ensembles (MI, MP and MR) of future d4PDF data in the periods of 2051-2070 and 2091-2110. In general, the corrected future rainfall data have a

difference caused by the adjustment of parameter values based on both original d4PDF data and observation.

For the period 2051-2070, the maximum and minimum of annual rainfall amounts for MI, MP and MR ensembles are shown in Figures 4.9 and 4.10, respectively. A similar annual rainfall trend of MI and MP ensembles is remarkable at most gridded cells in a mean range of 1,300-3,080 mm/year. However, the minimum annual rainfall amount of MP ensemble is lower than the MI ensemble about 200 mm/year at the location of Bhumibol Dam and mid-stream of Yom River (Figures 4.9(a) and 4.9(b)). For the MR ensemble, about 550-2,600 mm/year is the range of minimum annual rainfall at all grid cells in Figure 4.9(c). Lower than 1,000 mm/year is identified the most area of Ping River basin. This low rainfall intensity might affect to water scarcity in the basin and Bhumibol dam in the future. And, the maximum annual rainfall of all ensembles (Figure 4.10) is higher than 3,000 mm/year at upstream of Ping River. On Nan River Basin, Pasak River Basin, and Lower CPRB, the range of 1,700-2,000 mm/year is the maximum annual rainfall. In other basins, the maximum annual rainfall values are variously about 2,000-3,000 mm/year. Consequently, the large inconsistency of rainfall intensity in all areas of the CPRB has captured by the MR ensemble for both minimum and maximum trends.

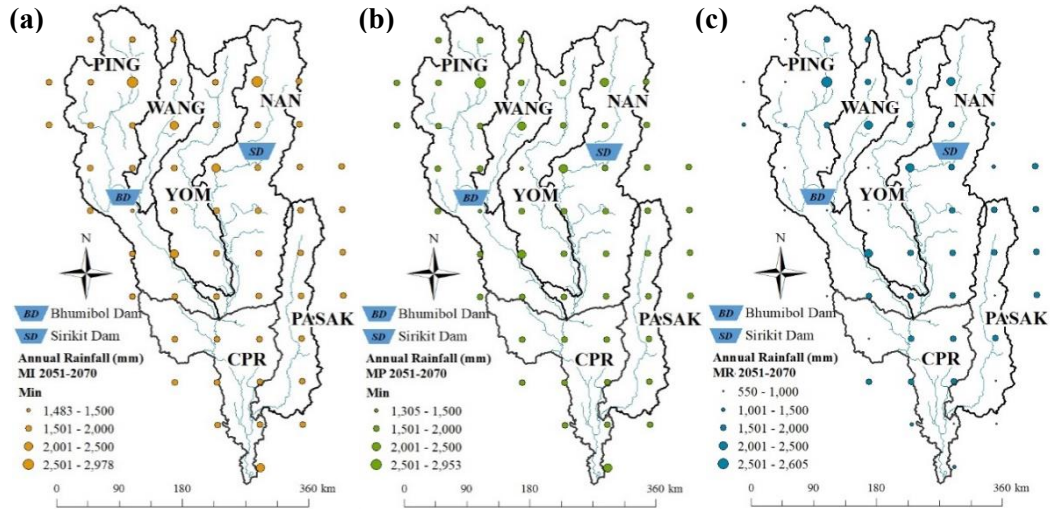


Figure 4.9 Minimum ranges of the annual rainfall of years 2051-2070 at 57 grid cells through (a) MI ensemble, (b) MP ensemble, and (c) MR ensemble

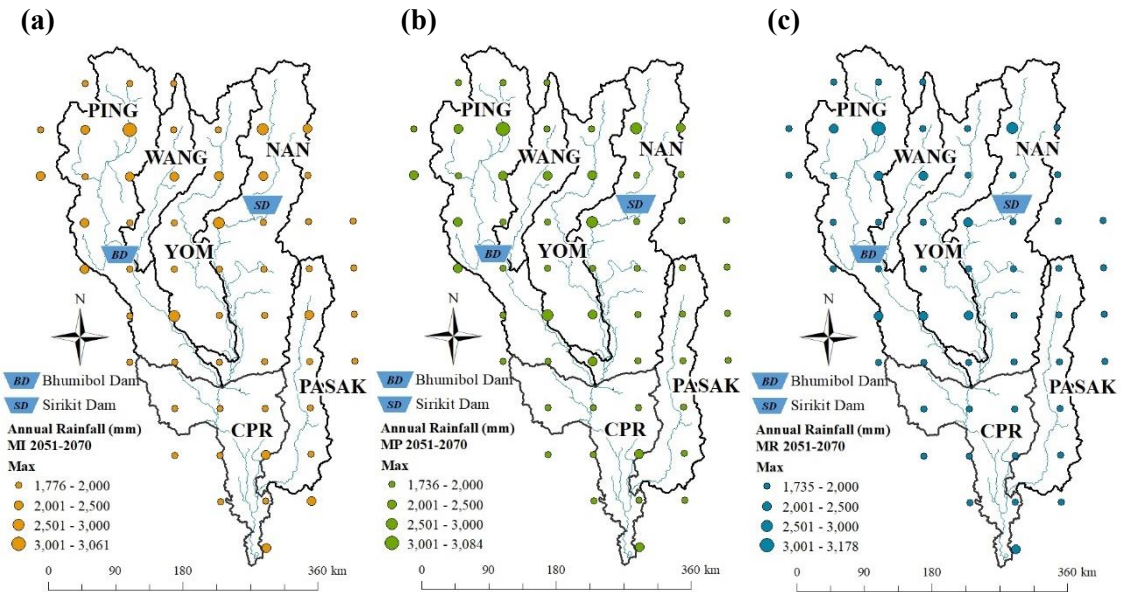


Figure 4.10 Maximum ranges of the annual rainfall of years 2051-2070 at 57 grid cells through (a) MI ensemble, (b) MP ensemble, and (c) MR ensemble

The annual rainfall for the period 2091-2110 for three ensembles (MI, MP and MR) is between 1,600 and 3,000 mm/year on average. Noticeable, the minimum annual rainfall of MI is close to that of MP ensembles for most grid stations in Figures 4.11(a) and

4.11(b). However, the difference of minimum annual rainfall range is observed significantly at the lower part of the Nan River Basin that MP ensemble has lower rainfall values approximately 500 mm/year. For the MR ensemble, the minimum rainfall values are lower than these in other ensembles (Figure 4.11(c)); thus, the low rainfall accumulation in the range of 500-1,000 mm/year may be a good preference for predicting extreme situations of water scarcity in the future. In particular, the rainfall intensity at the upstream of the Bhumibol Dam is very low. For the maximum annual rainfall, a range of 2,500-3,060 mm/year in MI and MP ensembles (Figures 4.12(a) and 4.12(b)) is observed at the upper parts of Ping and Nan River Basins. This high rainfall intensity in the upstream could affect the operation of both the Bhumibol Dam and Sirikit Dam.

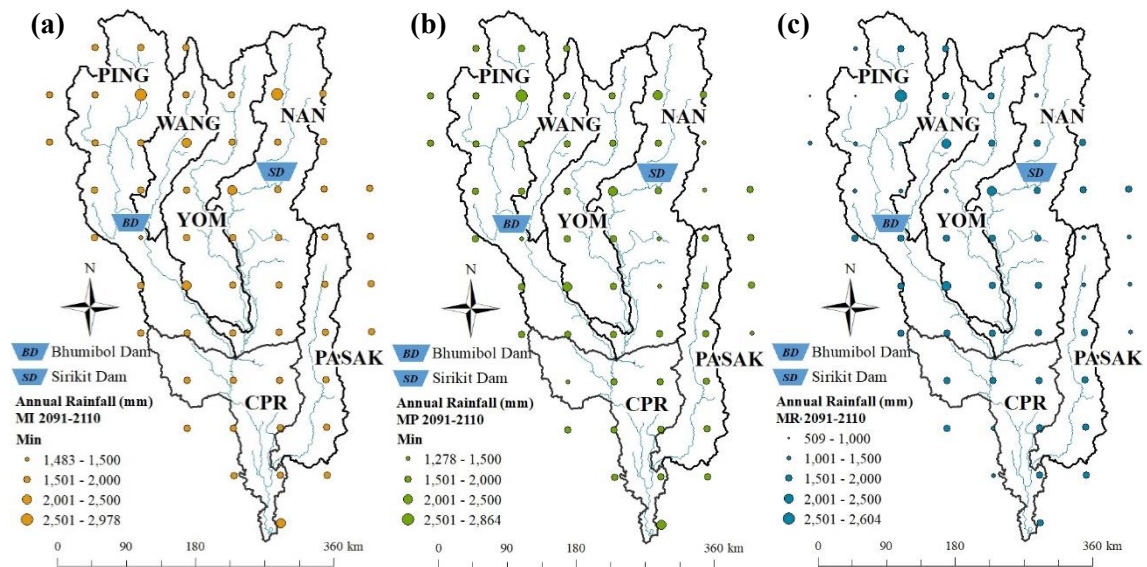


Figure 4.11 Minimum ranges of the annual rainfall of years 2091-2110 at 57 grid cells through (a) MI ensemble, (b) MP ensemble, and (c) MR ensemble

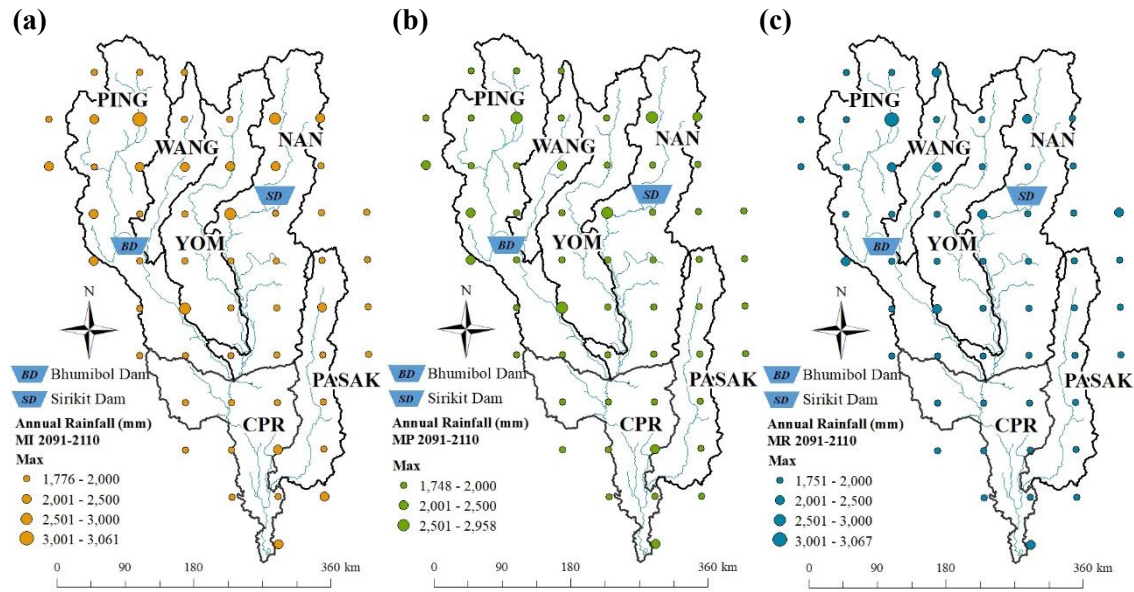


Figure 4.12 Maximum ranges of the annual rainfall of years 2091-2110 at 57 grid cells through (a) MI ensemble, (b) MP ensemble, and (c) MR ensemble

The overall consistency of rainfall intensity, approximately 1,000-2,000 mm/year of minimum and maximum annual rainfall, is resulted in the downstream Nan River, Pasak River Basin, and Lower CPRB. More specially, the lowest and highest annual rainfall amounts are about 510 and 3,170 mm/years, respectively, showing first and foremost in Ping River Basin. Consequently, the Ping River Basin might obtain more frequency of both floods and droughts in the future.

4.3.2.2 Bias Correction for Atmospheric Temperature

Due to the large difference in temperature values between the observed and original d4PDF data as shown in (Figures 4.13(a) and 4.14(a)), a bias correction is necessary to reproduce the observed rainfall pattern. In this research, the Equidistant Cumulative Distribution Function Matching (EDCDFm) method, in which the d4PDF temperature ranges are adjusted by the observation distributions at all grid cells, was used to reproduce

maximum and minimum temperatures. Historical temperature data of a grid cell, located in the Lower CPRB, are an example to result in maximum and minimum trends as illustrated in Figures 4.13 and 4.14, respectively.

For the daily maximum temperature of historical d4PDF data for the years 2000-2010 in Figure 4.13(a), the temperature is between -15 and 46 °C, while the maximum temperature of observation is in the range of 23-42°C. After the bias correction, the d4PDF temperatures are corrected to a similar trend of the observation that the corrected temperature is about 24-41°C, as shown in cumulative distribution function by the red line in Figure 4.13 (b). The EDCDFm method is very effective in order to reduce the d4PDF model biases.

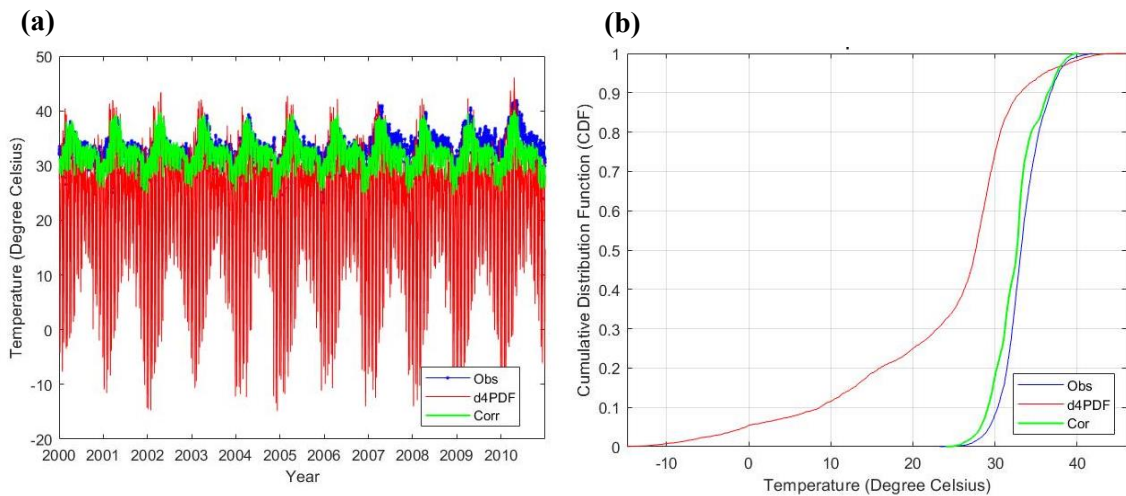


Figure 4.13 Observed, d4PDF and corrected data of the years 2000-2010 for **(a)** daily maximum temperature and **(b)** cumulative distribution functions at a grid station located in Lower CPRB

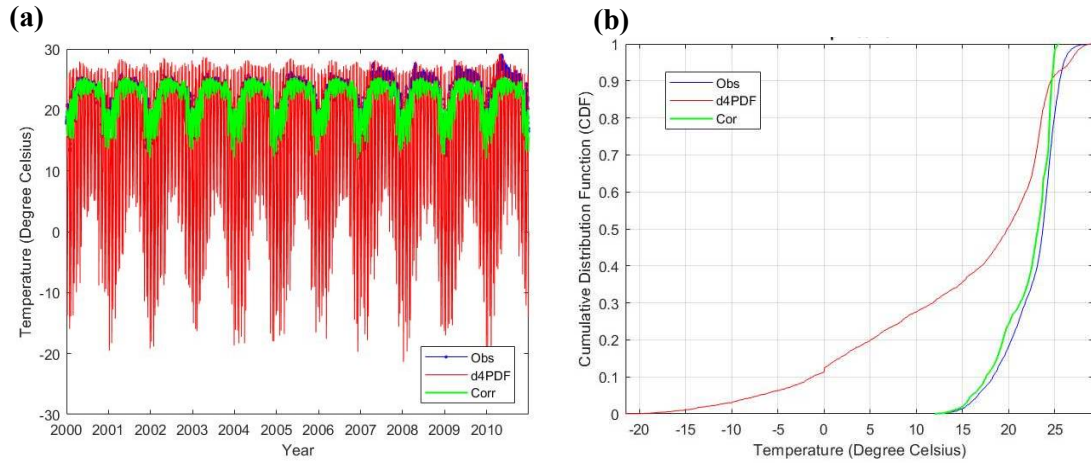


Figure 4.14 Observed, d4PDF and corrected data of the years 2000-2010 for **(a)** daily minimum temperature and **(b)** cumulative distribution functions at a grid station located in Lower CPRB

In contrast, due to the large variability of original d4PDF data, the minimum temperature range between -22 to 29 °C, which is about 12-29 °C in observation data, as illustrated in Figure 4.14(a). Figure 4.14(b) shows the corrected minimum temperature that could be adjusted to be 12-26 °C on the basis of the observed distribution. More specifically, the highest value of minimum temperature is widely underestimated above the 90th percentile because the d4PDF output is higher than the observed value. In Equation 4.6, the corrected output bases on the d4PDF output and the observed distribution. When the d4PDF temperature is 28°C, the corrected output can be 26°C if the inverse distributions of observation and d4PDF model are in the difference of 2 °C (Figure 4.14(b)).

For the temperature trends in the CPRB, the averages of the annual maximum temperature of observed, d4PDF, and corrected data are shown in Figure 4.15. The high values of observed temperature indicate in the middle parts of Wang River Basin and Lower CPRB in Figure 4.15(a), due to the effects of the topography and lower elevation

than the surrounding areas. For the northern part of the Ping River Basin, the lowest temperature of observation indicates since the high elevation above 2,000 m of the mean sea level. Conversely, the maximum temperature patterns of observation and d4PDF model are totally different tendency for the whole basin (Figure 4.15(b)). The higher values of d4PDF temperatures are at the north part of Yom and Nan River Basin since the simulations of sea surface temperature and wind direction in the d4PDF model differ from the actual temperature pattern. After bias correction, the average maximum temperature tends to become similar to the observation pattern, particularly at the highest and lowest maximum temperatures (Figure 4.15(c)). Noticeably, the corrected means are slightly lower than the observations about 3 °C with the reason explained in Figure 4.14.

In regards to the minimum temperature (Figure 4.16), the observed temperatures have low values at the north part of CPRB, and the high values are around the central part of Upper CPYRB and downstream of Lower CPYRB. Figure 4.16(b) illustrates the minimum temperature of d4PDF output. The low values identify at the most area of Ping and Wang River Basins. In the improvement through the bias correction approach, the trend of the corrected minimum temperature is similar to the observation, but the corrected means are undervalued at approximately 2°C. Without bias correction, the d4PDF temperature outputs at all grid cells are shown in a dissimilar pattern from the observation distribution. Bias correction using the EDCDFm method is accordingly very effective in reducing d4PDF model biases and capturing local temperature pattern in each area of the CPRB.

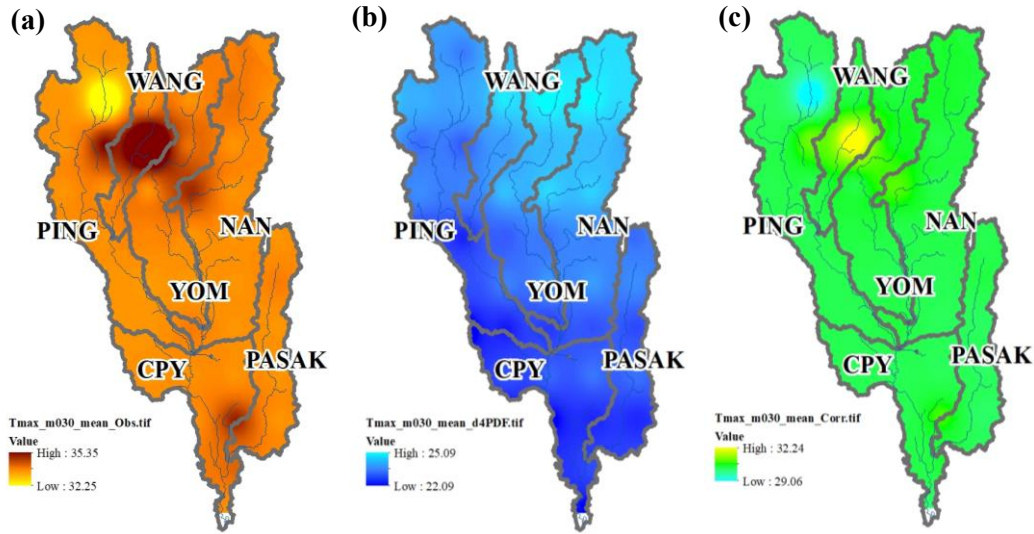


Figure 4.15 Average annual maximum temperatures ($^{\circ}\text{C}$) of (a) observation, (b) d4PDF model, and (c) corrected output

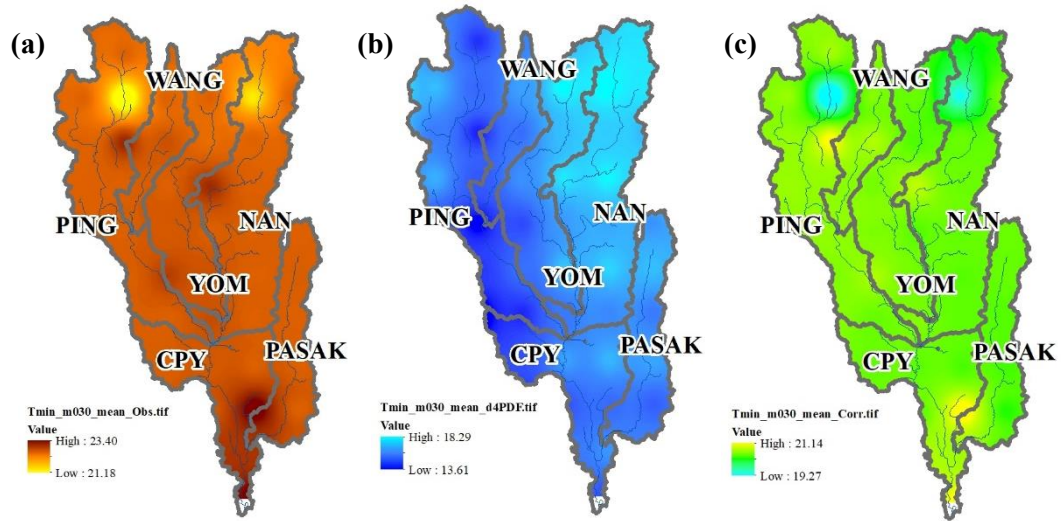


Figure 4.16 Average annual minimum temperatures ($^{\circ}\text{C}$) of (a) observation, (b) d4PDF output, and (c) corrected output

4.4 Summary

The post-processing techniques of d4PDF model, including interpolation and bias correction methods, have been developed in the context of the conditions of the CPRB.

The interpolation using Gradient-plus-inverse-distance-squared (GIDS) method has successfully performed the observations of 22 met gauge stations transformed into 57 gridded cells. Bias correction approaches for rainfall have been developed in terms of time windows, seasonality and month. In this chapter, we found that the gamma distribution approach with setting monthly time window for dry season datasets and the gamma distribution combined with a Generalized Pareto Distribution (Gamma & GPD) approach with using seasonal time window for rainy season datasets could overcome three important issues; (1) producing extreme rainfall events, (2) expanding dry days during the dry season, and (3) intensifying rainfall amounts during the rainy season.

After the bias correction of historical rainfall data for the years 2000-2010, the accumulated rainfall means of corrected data are slightly underestimated in comparison of the observation. After the bias correction of future rainfall of three ensembles, the MI and MP ensembles indicate a similar trend of annual rainfall. Especially in most areas of the Ping River Basin, about 500-1,000 mm/year of annual rainfall is predicted through the MR ensemble. The high amounts of the maximum annual rainfall of three ensembles above 3,000 mm/year are predicted in the up-streams of Ping and Nan River Basins. As results, all ensembles of future rainfall outputs reproduced by developed bias correction approaches may predict extreme rainfall, including the lowest and highest amounts.

For atmospheric temperature, the Equidistant Cumulative Distribution Function Matching (EDCDFm) method, which is a different bias correction method from rainfall, is an effective approach to correcting the maximum and minimum temperatures of the d4PDF model. Wide variability between the observation and the d4PDF model has been reported. The d4PDF data were adjusted in a similar pattern with observation after the

bias correction method. Particularly, the corrected maximum and minimum temperatures are underestimated about 2-3 °C.

Given the main research objective to investigate the impacts of future climate change, the corrected datasets of both daily rainfall and temperature are important inputs to simulate climate-adaptive pond management, reservoir operation, and frequencies of flood and drought in Chapters 5, 6, and 7, respectively.

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Chapter 5

Pond Designs and its Effective Operations

Considering Long-term Impacts of Climate Change and Economy

5.1 Introduction

The increasing frequency of extreme rainfall causes high flows and flood occurrences, while human activities influence on the normal range of rainfall amount (Loucks and Beek, 2017). The planning of the activities and flood risk management should be involved in water resources management. Strategies of water resources management play an essential role in mitigating risks and meeting water demands. Ponds are an important alternative water resource given a specific purpose (*e.g.*, agriculture, aquaculture, flood control, recreation, *etc.*). In the view of the agricultural objective, on-farm pond management, in general, focuses on crop irrigation demand and pond water availability (Ouyang *et al.*, 2018). Within the expectation of sustainable yields of crop production, one of the main limitations is the scarcity of water during the dry season. During the rainy season, the overflow can be massive damages to agriculture production. However, the pond overflow and water scarcity are limitedly explored how ponds can be managed to mitigate the situations by year-to-year basis. This can be accomplished by constructing agricultural ponds, considering the storage and provision of irrigation water throughout the farm areas.

Currently, the demands for the construction of ponds in Thailand, including the Chao Phraya River Basin (CPRB) continues to rise due to not only increased water consumption but also the supports and promotions from Thai Government as the details explained in Chapter 1. Devoting a high number of ponds in the basin would change the river discharges. To meet water demands and to protect overflows and droughts, the uses of agricultural ponds are a challenge. Great protection against flooding in ponds connected with an irrigation purpose should be advised. However, a few information and guidance documents considered to be reliable local conditions for the construction of ponds in Thailand are provided. Due to the lacks of information, this research aims to achieve three objectives: (1) to construct pond modelling in the combination of water requirements model and water budget model based on characteristics of Chao Phraya River Basin (CPRB), (2) to provide information of pond designs and propose appropriate pond operations considering long-term impacts of climate change, and (3) to determine the numbers of future ponds in terms of water resources management and economic aspect.

5.2 Model Formulas and Developments

The overall simple method as shown in Figure 5.1 is used to estimate pond designs and capacities, considering fluctuated water demand for an agricultural purpose, future climate change, protections for overflow and water scarcity, and economic viewpoint. Future climate data, the post-processing d4PDF outputs of 45 ensemble members from Chapter 4 corrected by the developed bias correction method, are the inputs to both water requirements model and water budget model. The water requirement model estimates monthly crop water requirements. In the water budget model, pond capacities are simulated by specific pond information and parameters such as locations, pond capacities,

land use, catchment areas, *etc.* Reliability of the pond is a crucial decision to estimate appropriate simulated capacities in this chapter. Moreover, the costs and benefits of pond constructions are assessed by the economic model.

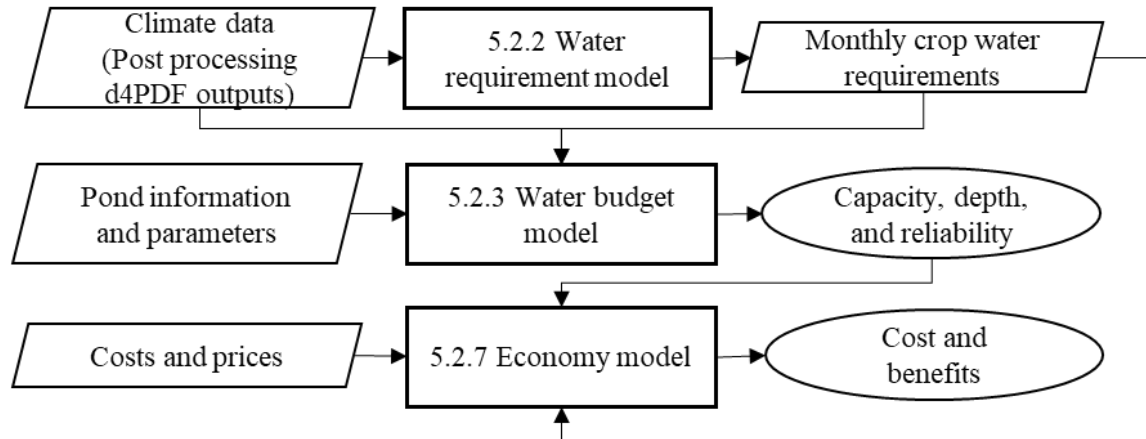


Figure 5.1 Overall methodology flowchart used in this chapter

5.2.1 Data information and Input parameters

In this research, historical and future climate data, comprising 45 ensemble member datasets, are required inputs in both the water requirements and water budget models as details described in Table 5.1. Moisture status and crop coefficients depend on the types of crops and period of crop growths recorded by the Royal Irrigation Department (RID) experiments. More specifically, the weekly crop coefficients are for rice and horticulture and the monthly crop coefficients for field, perennial and orchard crops. In the water budget model, curve number values were estimated by land use, hydrological conditions, and soil types. Pond information includes the capacity of the pond, surface area, and location. The information on public ponds were obtained from the Department of Water Resources (DWR) and that on private on-farm ponds were provided from the Land Development Department (LDD). The catchment area of a pond is an important parameter

in the model for estimating runoff into the pond. Digital Elevation Model (DEM) of a 90-meter resolution was used to estimate the catchment area of each pond by a GIS technical method. Regards to the economic model, the factors (*e.g.*, crop prices and yields) were used as secondary data provided by the Office of Agricultural Economics (OAE), Thailand.

Table 5.1 Hydrological data and input parameters in the models

Input and parameters	Note	Source
Hydrological conditions		
Daily rainfall		
• Observed data	2000-2010	Thai Meteorological Department
• Post processing d4PDF	45 ensemble members: 2000-2010, 2051-2070 and 2091-2010	d4PDF
Daily evaporation	45 ensemble members: 2000-2010, 2051-2070 and 2091-2011	Hamon method (Martel <i>et al.</i> , 2018)
Water Requirements Model		
Moisture status	1 mm/day for rice and 2.5 mm/day for crop	RID, n.d.
Crop coefficient	Five crop types	Hargreaves, 1995; RID, 2011
Water Budget Model		
Curve number	68-88 for Agriculture, 58-59 for paddy field, 74-93 for the forest, 54-77 for urban and 39-68 for water body	USDA, 1997
Seepage rate	4.43 mm/day for the dry season and 3.32 mm/day for the rainy season	Nath and Boite, 1998
Pond capacity, surface area and location		DWR and LDD
Catchment	DEM (3 arc-second, 90 meters)	Estimated
Economic Model		
Crop prices and yields	2010-2019	OAE
Land-use data		LDD
Yield response factors		Allen and FAO, 1998
Pond construction costs		CGD, 2018

5.2.2 Water Requirement Model

Estimating the crop water requirements have been suggested to calculate crop water needs by multiplying the potential evapotranspiration with crop coefficient as in Equation 5.1a.

$$ET = K_c \times ET_0 \quad (5.1a)$$

ET : Actual evapotranspiration (mm/day)

K_c : Crop coefficient

ET_0 : Potential evapotranspiration (mm/day)

Regards to the potential evapotranspiration (ET_0), Royal Irrigation Department, Thailand has calculated ET_0 and estimated the crop coefficient (K_c) for seven methods: Modified Penman, E–pan, Penman Monteith, Blaney Criddle, Thornthwaite, Hargreaves, and Radiation (RID, 2011). The data requirements for the seven methods are different, but the temperature is mainly required for all methods. The Hargreaves method was used in this research due to the limitation of the observed data. Equation 5.1b calculates the irrigation amount.

$$Irr = ET - ER + M \quad (5.1b)$$

Irr : Irrigation amount (mm/day)

ET : Actual evapotranspiration (mm/day)

ER : Effective rainfall (mm/day) is estimated by the USDA Soil Conservation

Service (SCS) method in Equations 5.1c and 5.1d (USSCS, 1972; RID, 2006).

$$ER = R \left(\frac{125 - 0.2R}{125} \right), R < 250 \text{ mm} \quad (5.1c)$$

$$ER = 125 + 0.1R, R > 250 \text{ mm} \quad (5.1d)$$

M: moisture status (mm/day) were set 1 mm/day of rice and 2.5 mm/day of the crops during the dry season (RID, 2011)

5.2.3 Water Budget Model

In the model, the basic water budget equation is used to estimate changes in water volume at which inflows (daily rainfall and runoff) minus outflows (seepage, evaporation, and estimated water demand) at a time interval as calculated using Equation 5.2.

$$\Delta V = P + RO - S - E - WR \quad (5.2)$$

ΔV : Change in storage volume (m³)

P : Daily rainfall (m³)

RO : Runoff is calculated in Equations 5.3a and 5.3b

S : Seepage is calculated in Equation 5.3c

E : Evaporation (m³)

WR : Pond water for irrigation related to crop water requirements in Equation 5.4

Estimated runoff (RO) is calculated by the US Soil Conservation Service (USSCS) curve number method involving the conditions of soil moisture, soil group, and land use in Equation 5.3a (USSCS, 1972). Watershed area and hydrological condition relate to the runoff estimation as in Equation 5.3b.

$$w_r = \left(\frac{1000}{CN} - 10 \right) \times 25.4 \quad (5.3a)$$

$$RO = W \left(\frac{(p_d - 0.2w_r)^2}{p_d + 0.8w_r} \times \frac{1}{1000} \right) \quad (5.3b)$$

CN: Curve number

w_r : Maximum watershed retention (m/day)

W : Effective pond catchment area (m²)

p_d : Daily rainfall (m/day)

Seepage (S) is calculated by daily seepage rate and the surface area of pond in Equation 5.3c. In the model, daily seepage rate was set to be 4.43 mm/day during the dry season, and 25 percent of the seepage rate is decreased during the rainfall events as this information has reported for ponds in Thailand by Nath and Boite (1998).

$$S = \frac{AS_r}{1000} \quad (5.3c)$$

S_r : Daily seepage rate (m/day)

A : Pond surface area (m²)

5.2.4 Pond Operation Rules

The pond operation rules in this research were designed in considerations of the water demands from farmers and protection against floods and droughts. The water demands were estimated by crop water requirement relevant to different crop types in the water requirements model. The monthly water requirements are a parameter to assess pond water withdraw at which maximum water requirement of dry season period from November to April was assumed to be the pond capacity in Equation 5.4a. With the assumption in which the dry seasonal water requirements equal to the pond capacity, the monthly irrigation water (WR) during the dry season is estimated by how much water in percentage of the capacity withdraws from the pond (Figure 5.2). In contrast, during the rainy season from May to October, a small amount of irrigation water is generally required. Thus, the ratio of water requirements between the rainy season and dry season was designed for pond irrigation water (WR) as in Equation 5.4b. In these equations, the percentages of monthly water requirement per a seasonal water requirement at the month m in the year y are estimated the fluctuating water withdraws in considering day-to-day

hydrological conditions. The change of pond volume at the daily interval was then evaluated by a loss of the pond water for irrigation by Equation 5.2.

$$WR = P_{Dry,m,y} \times C \quad \text{for the dry season} \quad (m \geq 11 \text{ and } m \leq 4) \quad (5.4a)$$

$$WR = P_{Rain,m,y} \frac{S_{Rain,y}}{S_{Dry,y}} \times C \quad \text{for the rainy season} \quad (5 \leq m \leq 10) \quad (5.4b)$$

WR : Pond irrigation water related to crop water requirements (m^3)

C : Pond capacity (m^3)

$P_{Dry,m,y}$: Monthly water requirement per dry seasonal water requirement

$P_{Rain,m,y}$: Monthly water requirement per rainy seasonal water requirement

$S_{Dry,y}$: Dry seasonal water requirement (m^3)

$S_{Rain,y}$: Rainy seasonal water requirement (m^3)

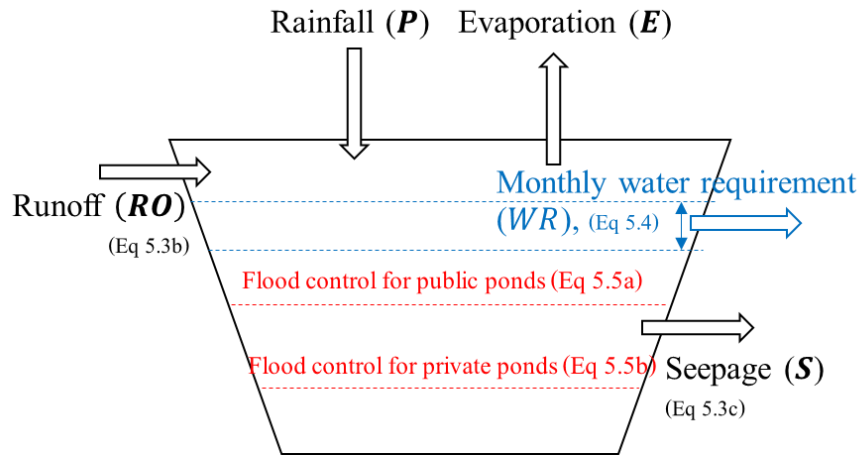


Figure 5.2 Pond hydrological process and operation rules

Protection against floods and droughts has also been taken into account in the pond operation rules. As far as the operation rule for public ponds is concerned, 50% of capacity was created to maintain water volume in June or at the beginning of the rainy season (Equation 5.5a). The pond has space for the half size of pond to protect the overflows at the end of the rainy season and to keep water for the next dry season. Twenty

percent of the pond capacity was also commanded to have water for public ponds in Equations 5.5b and Figure 5.2. The different percentages for public and private ponds have been considered for the purpose of the pond. The objectives of private ponds are for agricultures, aquacultures, water utilizes, recreation, *etc.* In contrast, the agricultural irrigation is only one purpose for the private ponds.

$$V_t = 0.5 \times C \text{ for public ponds} \quad (5.5a)$$

$$V_t = 0.2 \times C \text{ for private ponds} \quad (5.5b)$$

V_t : storage in the pond (m³)

C : Pond capacity (m³)

5.2.5 Pond Reliability

Reliability is an assessment to decide the faults of pond operations and inappropriate pond design. In the model, if the water volume is less than 20 percent of pond capacity assigning for pond water scarcity and more than 90 percent of the capacity for overflow occurrence, the failure is calculated at the day in Equation 5.6 (Mehta and Goto, 1992).

$$\text{Reliability (\%)} = (T - F) \times \frac{100}{T} \quad (5.6)$$

T : Total number of simulated days

F : Number of failure days

5.2.6 Estimating Numbers of Future Ponds

In order to optimize agriculture production, irrigation water should be meet its water demands. Thai government has envisioned that ponds are important water resources for agriculture because of cheaper irrigation transportation costs, less losses of water, and more effective irrigation. Accordingly, the Land Development Department (LDD) has formed the Free Pond Construction Project for non-irrigated areas since 2005. A total of

68,177 ponds have been built in the CPRB, and more than 58,000 ponds are planned to be built in the future. Pursuant to the Government Plan, the aim of this chapter is to suggest appropriate numbers of future ponds in each sub-district. Consequently, the number of future ponds is estimated by an insufficient amount of irrigation as calculated by Equation 5.7.

$$IRR_{Y,s} = IRR_{Y,Dry,s} - I_{r,s} \times IRR_{Y,Dry,s} - C_{GV,s} - C_{PV,s} \quad (5.7a)$$

$$N_{p,s} = \frac{IRR_{Y,s}}{C_{New,s}} \quad (5.7b)$$

$IRR_{Y,s}$: Insufficient irrigation amount (m^3)

$IRR_{Y,Dry,s}$: Dry seasonal irrigation amount (m^3)

$I_{r,s}$: Irrigation areas in percent

$C_{GV,s}$: Total capacity of the public ponds (m^3)

$C_{PV,s}$: Total capacity of the private ponds (m^3)

$C_{New,s}$: Suggested capacity of the future pond (m^3)

$N_{p,s}$: Number of future ponds

Aforementioned dry seasonal crop water requirements (Equation 5.1b) were assumed to be the maximum water demands, the insufficient irrigation amounts at sub-district s were calculated by taking into account the current irrigation water from canals and rivers ($I_{r,s} \times IRR_{Y,Dry,s}$) and pond waters ($C_{GV,s}$ and $C_{PV,s}$). Specifically, the simulated capacities of public ponds ($C_{GV,s}$) and private ponds ($C_{PV,s}$) were considered to be a larger size than the actual pond capacity; on the other hand, if the simulated capacity is smaller, the actual pond capacity was used in the Equation 5.7a. Suggested pond capacity ($C_{New,s}$) at the sub-district s was assessed by the Equation 5.7b. Finally, the results of the number of future ponds ($N_{p,s}$) at the sub-district s could be useful for future government plans.

5.2.7 Economic Model

When investing a large amount of budget in infrastructure projects, governments need to consider and research long-term effects on several dimensions such as government revenues, expenditures and various impacts on productions. Economic cost-benefit analysis strategy is an alternative method that governments always use to evaluate the projects on the basis of worthwhileness and changes in economic growth. In the context of huge investment projects of water resources management, this chapter aims to use the economic model to assess the allocation of water use related to agricultural impacts. With regards to future pond constructions, the benefits relate to the changes of future agricultural productivities and the main direct costs were evaluated by construction costs of future ponds, which are based on the previous results of selected pond designs in each sub-district.

5.2.7.1 Benefits

The benefits of pond constructions of 2,024 sub-districts are mainly changes in crop productions. In terms of crop productions, five crop types (*i.e.*, rice, field crops, perennials, orchards and horticulture) were estimated by the changes of crop yields, average crop prices, and factors of maximum expected crop yields as in Equation 5.8. In consideration of the crop patterns, the rice productions were assumed to increase by which farmers could cultivate the off-seasonal rice. The off-seasonal rice plantation was assumed to use irrigation water from future ponds. As a result, the increases in rice productions were predicted by Equation 5.8a. Other crops were estimated in a different equation (Equation 5.8b) since these crops are generally planted all year.

$$\sum_{s=1}^{2024} \sum_{j=1} Ac_{s,j} \times [(Y_{sj} \times P_j) - PC_j] \quad \text{for rice} \quad (5.8a)$$

$$\sum_{s=1}^{2024} \sum_{j=2}^5 Ac_{s,j} \times \text{mean}[\sum_{k=2}^{11} (Fm_{ik} - 1) \times Y_{s,k} \times P_k] \quad \text{for other crops} \quad (5.8b)$$

Y : Actual crop yield (kg/m²)

P : Price per unit of crop (Baht/kg)

PC : Production costs (Baht/m²)

Ac : Area of the crop field (m²)

Fm : Factor of average value of maximum expected crop yields of the crop type j

s : Sub-district (2,024 sub-districts in Chao Phraya River Basin)

j : Crop types (rice, field crops, perennials, orchards and horticultures)

k : 11 crops in the model (rice, pineapple, sugarcane, cassava, banana, lemon, para, logan, orange, bean, and corn)

Due to the conditions of hydrology, soil moisture and available water supply, the actual crop yields (Y) were used by district/province data that were recorded in 2018 by Office of Agricultural Economics (OAE), Thailand. Also, the crop prices and crop production costs were used secondary data, which have been recorded over ten years of data by OAE. The crop areas were reclassified by land-use data as obtained from the Land Development Department (LDD). In order to estimate changes in crop productivities, crop yields may be increased by more irrigation water during the crop growth period. Due to the relationship between water supply and crop productivity, an equation of yield response to the water was developed in this research to estimate maximum expected crop yield factor as (Fm) in Equation 5.8c (Doorenbos *et al.*, 1979).

$$Fm_{s,k} = \frac{1 - [K_{y,k} \times (1 - \frac{ET_{c2}}{ET_m})]}{1 - [K_{y,k} \times (1 - \frac{ET_{c1,s,k}}{ET_m})]} \quad (5.8c)$$

$K_{y,k}$: Yield response factor of the crop k

ET_m : Maximum evapotranspiration

$ET_{c1,s,k}$: Current evapotranspiration of the crop k at sub-district s

ET_{c2} : Expected evapotranspiration

The yield response factors ($K_{y,k}$) have been recorded by FAO Irrigation and Drainage Paper No.33 and No.56, (Allen and FAO, 1998; FAO, 2012). In the model, the current evapotranspiration ($ET_{c1,i,k}$) depends on irrigation area and effective growing season precipitation in each sub-district. In general, effective rainfall during the growing season could support 60% of maximum evapotranspiration (ET_m). And 100% of irrigation area in the sub-district s is assumed to additionally increase 30% of ET_m . If the irrigation area decreases, the value of $ET_{c1,i,k}$ is also decreased as the proportion of irrigation area. Hence, the current evapotranspiration values were estimated at 60-90% of ET_m . With the same assumption, the high effective irrigation from the future ponds could increase the expected evapotranspiration (ET_{c2}) to be 90% of ET_m at all sub-districts.

5.2.7.2 Costs

In the scope of this research, pond constructions are the main investment costs contributed to the costs of excavation, dykes, grass plantation, leakage protection and maintenance. Excavation volume and leakage protection were estimated at 80% and 5% of a pond capacity as in Equations 5.9a and 5.9b, respectively (RID, 2003). Dykes for use of soil volume (Equation 5.9c) and grass plantation for planting area (Equation 5.9d) were calculated from the pond design as assumed to be trapezoidal shape pond. The direct costs were estimated as followed by the regularity of cost estimation for irrigation constructions, acquired from the Comptroller General's Department, Thailand (CGD, 2018). Since the construction costs depended on the price of petrol, the price was determined to be 5% higher than the current price. The estimated construction costs for excavation, leakage

protection, dykes, and grass plantation are 18.39 Baht/m³, 50.56 Baht/m³, 119.72 Baht/m³, and 44.60 Baht/m², respectively (CGD, 2018). In addition, maintenance costs require to include in the total direct cost. In general, the cost was estimated to be 5% of the investment cost for every five years after the construction that a single-sum present worth factor used the calculation in Equation 5.9e (Yates, 2005). Hence, the estimation of all investment costs in each sub-district s could be calculated using Equation 5.9f.

$$C_{E,s} = 0.8 \times 18.39 \times C_s \quad (5.9a)$$

$$C_{L,s} = 0.05 \times 50.56 \times C_s \quad (5.9b)$$

$$C_{D,s} = 119.72 \times (4A_s H^2 + 10H A_s + 1.12A_s) \quad (5.9b)$$

$$C_{G,s} = 44.6 \times (1.73H A_s + 4.47A_s) \quad (5.9c)$$

$$C_{I,s} = \sum_{n=5:5:30} \{ (C_{E,s} + C_{L,s} + C_{D,s} + C_{G,s}) \times (P/F, i\%, n) \} \quad (5.9e)$$

$$NC_s = (C_{E,s} + C_{L,s} + C_{D,s} + C_{G,s} + C_{I,s}) \times N_{p,s} \quad (5.9f)$$

NC_s : Net cost of the sub-district s

A_s : Pond area at the sub-district s (m²)

H : Dyke height assumed at 1 m.

C_s : Pond capacity at the sub-district s (m³)

$C_{E,s}$: Excavation cost (Baht)

$C_{L,s}$: Cost of leakage protection (Baht)

$C_{D,s}$: Cost of dykes (Baht)

$C_{G,s}$: Cost of grass plantation (Baht)

$C_{I,s}$: Cost of maintenance (Baht)

$(P/F, i\%, n)$: single-sum present worth factor $\left[\frac{1}{(1+i)^n} \right]$ at $i=5\%$ and $n = 30$ years

$N_{p,s}$: Number of future ponds

s: Sub-district (2,024 sub-districts in CPRB)

5.2.7.3 Cost-Benefit Ratio

In this research, the economic model has been applied to the considerations of the results of pond designs and agricultural benefits associated with crop patterns. The cost-benefit assessment could be calculated in the general equation of Cost-Benefit ratio (Equation 5.10) as provided by Inter-American Development Bank (Dixon J. A, 2012).

$$B/C \text{ ratio} = \frac{\sum_{t=1}^n \frac{B_t}{(1+r_t)^t}}{\sum_{t=1}^n \frac{C_t}{(1+r_t)^t}} \quad (5.10)$$

The B/C ratio is calculated by summing up the benefits (B_t) and costs (C_t) at the same time horizon as evaluate in years (t). In the model, the discount rate (r_t) was pre-determined at 10%, and the project procedure period (n) is 30 years (RID, 2003; CGD, 2018).

5.3 Model Approach

In view of the selection of pond designs, historical and future climatic conditions over 50 years with 45 datasets were simulated, although the estimation of fluctuating water demands related to the monthly water requirements as calculated in the water requirement model. Irrigation waters and operation rules of flooding and water scarcity have proceeded in the water budget model. The investment costs and benefits of crop productions were then estimated by the economic model. Figure 5.3 illustrates the overall modeling processes in this research.

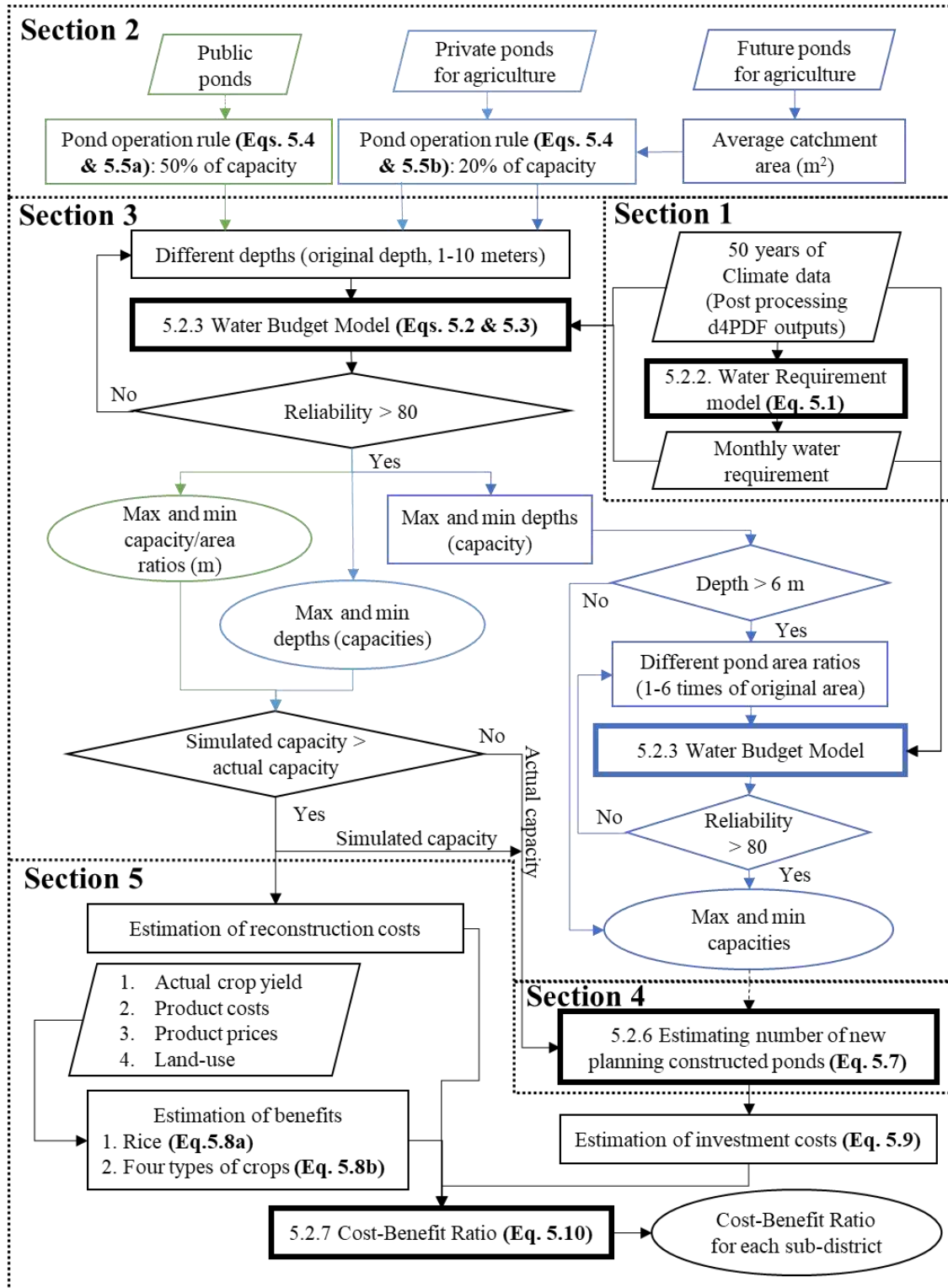


Figure 5.3 Model Approaches of the Water Requirement, Water Budget, and Economic Models

In section 1, the daily climate data (rainfall, maximum and minimum temperatures, and evaporation) from Chapter 4 were input in order to estimate the monthly water requirements (Equation 5.1), the changes of pond hydrological processes, and pond water volume (Equations 5.2 and 5.3).

Regarding section 2, pond information, including pond capacity, pond surface area, and other parameters are duplicated in Table 5.2. In the water budget model, 3,295 public ponds, 68,177 private ponds, and 2,024 units of future ponds have been simulated. In view of more specific details of future ponds, 2,024 units were created in the boundary of sub-district in which 2,024 sub-districts are situated at the CPRB. Since the locations of future ponds are not identified, we assumed that watershed pond area, local climate, and other parameters were based on the conditions of pond's sub-district. Then, pond information was input in the model. Pond operation rules of fluctuating pond water withdraw (Equation 5.4) and flood and drought controls (Equation 5.5) were commanded to estimate daily pond level. In order to manage the floods and drought controls, fifty percent of the public pond capacity and twenty percent of the private or future pond capacity maintain their water volumes at the beginning of the rainy season to keep more space.

Section 3 focuses on the determination of appropriate pond capacity in the water budget model. In changes of pond designs in the model, different depths from 1 to 10 meters controlled at 0.2 meters of depth interval were simulated for each pond. Additionally, the original depth of each public pond was simulated to confirm the reliability of the current pond. The appropriate pond depth was determined at higher pond reliability than 80 percent. The final results reflect maximum and minimum depths with their capacities. However, the depths of private ponds and future ponds more than 6

meters are not practical due to unprofessional pond management, water quality effects, and safety. In view of these reasons, the pond design in considering the change of pond area at which the pond depth is deeper than 6 meters, was re-simulated in different surface area ratios from 1-6 times of the original pond area controlled at 0.2 times of the ratio interval in the water budget model. In a decision similar to the selected depth of the pond, the pond reliability higher than 80 percent was determined to be proper maximum and minimum pond capacities.

After selecting appropriate pond design in each sub-district from section 3, the number of the new constructed ponds is estimated by Equation 5.7 in section 4. Given the maximum and minimum capacities of the ponds, the numbers of future ponds have also been estimated. The largest and lowest numbers of ponds in each sub-district are represented for both maximum and minimum capacities.

Given an economic aspect of future ponds construction in section 5, the benefits of crop production increases (Equation 5.8) and the investment costs estimation that the results of numbers of future ponds were calculated in Equation 5.9, computed the cost-benefit ratio in Equation 5.10. The cost-benefit ratio in each sub-district is represented for four cases: (1) constructing the largest numbers of future ponds with maximum pond capacities, (2) constructing the largest numbers with minimum pond capacities, (3) constructing the lowest numbers with maximum pond capacities, and (4) constructing the lowest number with minimum pond capacities.

5.4 Results and Discussion

With regards to the determination of appropriate pond designs on the basis of local conditions using the combinations of water requirements model and water budget model,

the maximum and minimum pond capacities at higher than 80% of pond reliability have resulted for three classifications of ponds (public, private and future ponds). Then, the numbers of future ponds with an economic aspect are also reported in every sub-district.

5.4.1 Appropriate Pond Capacities

5.4.1.1 Public Ponds

Within the scope of agricultural purpose, the 3,295 public ponds have been simulated in order to find the appropriate depths. Since these ponds not only supply water for agricultures but also occasionally support for other purposes such as aquacultures and water utilities, these ponds should not be at very low water level. According to the protection of low water level, the 50% of pond volume in the model was required to maintain water level during the rainy seasons for the purpose of flood protection. After the simulations, the selected pond ratios of capacity/area or depth are presented by the maximum and minimum values in Figures 5.4a and 5.4b, respectively.

At reliability higher than 80 percent, the minimum and maximum pond ratios (pond capacity/area) result between 1 meter and 4 meters at most areas of the middle part of CPRB and Lower CPRB. On the other hand, public ponds situated at the upper part of the basin particularly should have the pond capacity/area ratio at least 10 meters. Since public pond areas are generally larger than private ponds, ponds have a higher possibility to dry up. However, the ponds could straightforwardly overflow more frequently at the end of the rainy season. From Figures 5.4c and 5.4d, the ponds at lower than 80% of reliability are spread in the basin as represented in Figure 5.5.

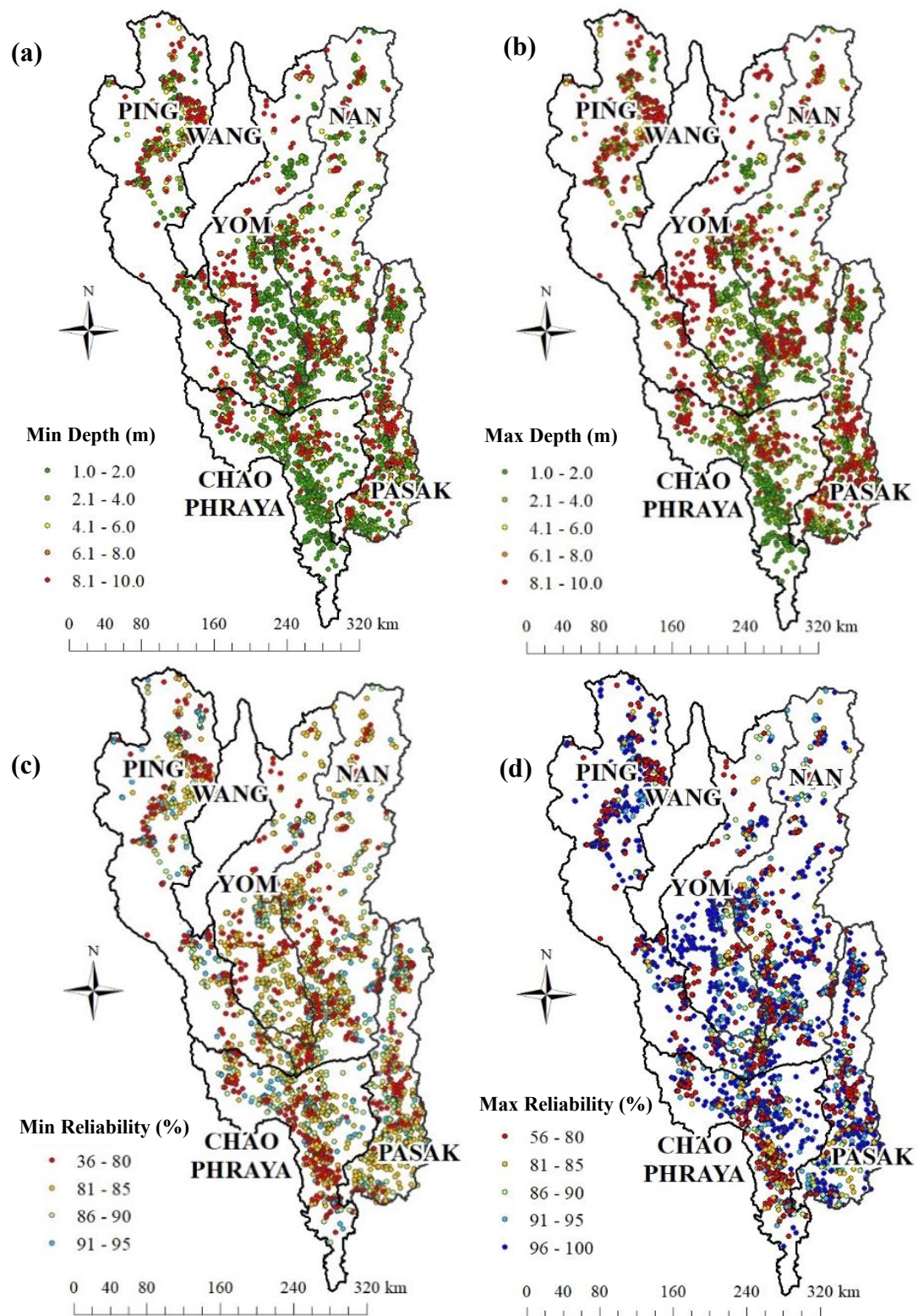


Figure 5.4 Suitable pond capacity/area ratios of public ponds, (a) minimum and (b) maximum values in meters and the reliabilities in percentage related to (c) minimum and (d) maximum pond ratios

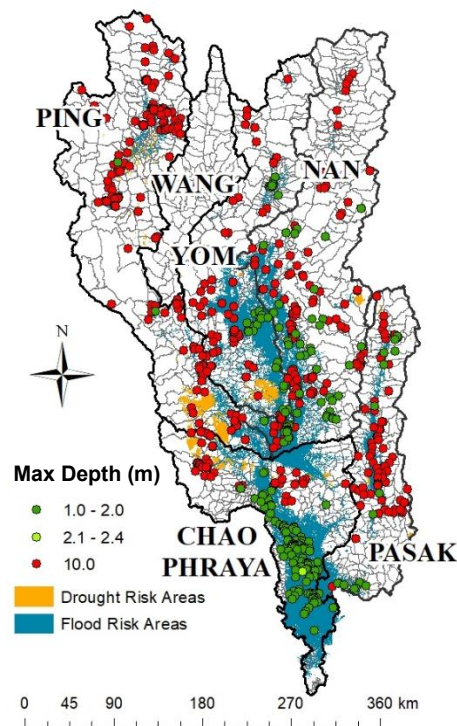
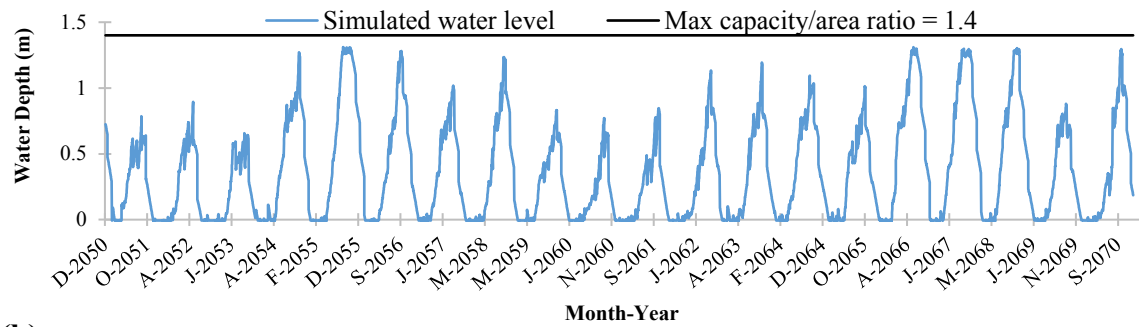


Figure 5.5 Maximum pond capacity/area ratio in meters at lower than 80% of pond reliability

The maximum capacity/area ratios between one meter and 2.4 meters (Figure 5.5) deliberated in the Nan River Basin and Lower CPRB. The deep ponds should be built at 10 meters or above in Ping, Yom and Pasak River Basins. Low-reliability ponds situated at flood and drought risk areas caused by the difficulties in maximizing irrigation waters related to agricultural growths and minimizing frequencies of flooding and droughts. Notably, the shallow ponds in which simulated results represent the pond capacity/area ratio of 1-2.4 meters (Figure 5.5) could dry up during the dry season (November-April) in Figure 5.6.

(a)



(b)

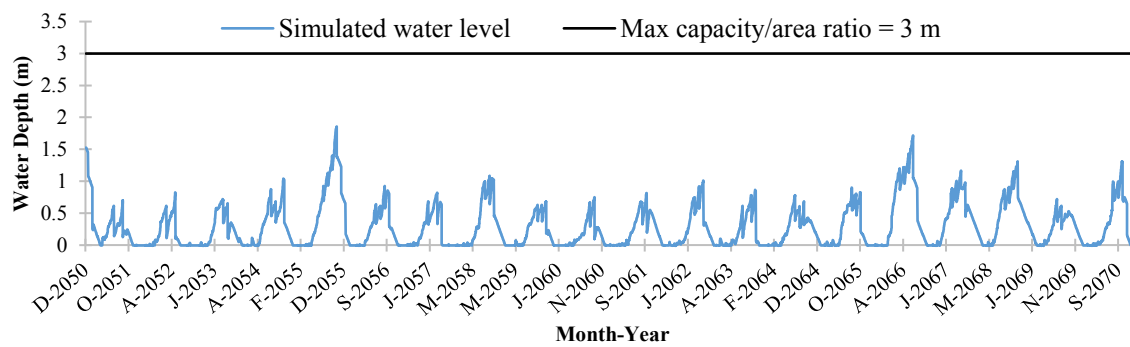


Figure 5.6 An example of increasing pond capacity/area ratio at (a) 1.4 meters and (b) 3 meters in which the pond locates in the Lower Chao Phraya River Basin

Figures 5.6a and 5.6b give examples of simulated pond water levels of the ponds locate in the Lower CPRB and having 78% of reliability. Due to the lower rainfall intensity and high water demands at Lower CPRB, even increasing pond capacity/area ratio or pond depth could not increase pond water levels. This is due to the limitation of the pond catchment area as shown in Figure 5.6b. Also, most areas of Lower CPRB are floodplain. Accordingly, the pond catchment areas, which affects runoff into the pond, are smaller than those in steep slope area. In this point of view, the pond could be received smaller water volume from runoff, and pond water level is mainly increased by rainfall. As results, the shallow ponds are an appropriate pond for construction in the floodplain areas.

5.4.1.2 Private Ponds

On-farm ponds of 64,599 units were constructed with a capacity of 1,260 m³ with an average pond area of 625 m², in the Free Pond Construction Project for non-irrigated areas by LDD. In order to determine appropriate pond capacity, the ponds with the specific pond area of 625 m² were simulated in the change of depths. Pond reliability was calculated at about 50 years of daily pond water levels. The results of minimum and maximum depths with reliability are shown in Figure 5.7.

The minimum and maximum capacities are 500-3,250 m³ and 1,800-3,250 m³, respectively. Focusing on above 80% of reliability, the minimum pond depth at each sub-district is heterogeneous in the basin due to the conditions of hydrology, topography, soil series, and land-use. The maximum depths for most sub-districts of the Chao Phraya River Basin illustrate between 8 meters and 10 meters, in which the reliabilities are higher than 90%. However, at a depth of 10 meters, lower than 80% of reliabilities for minimum and maximum depths in some sub-districts are obtained. Low-reliability causes by high annual rainfall above 2,500 mm in the northern part of CPRB as reported in Chapter 4. This result confirmed that deep ponds with specific pond area, 625 m², could not protect future overflows and droughts. Therefore, as results in changing the depths, pond depths at deeper than 6 meters with the high reliabilities are inappropriate for pond management. Thus, the future ponds in small scales are re-simulated in the combined changes of pond depths and areas.

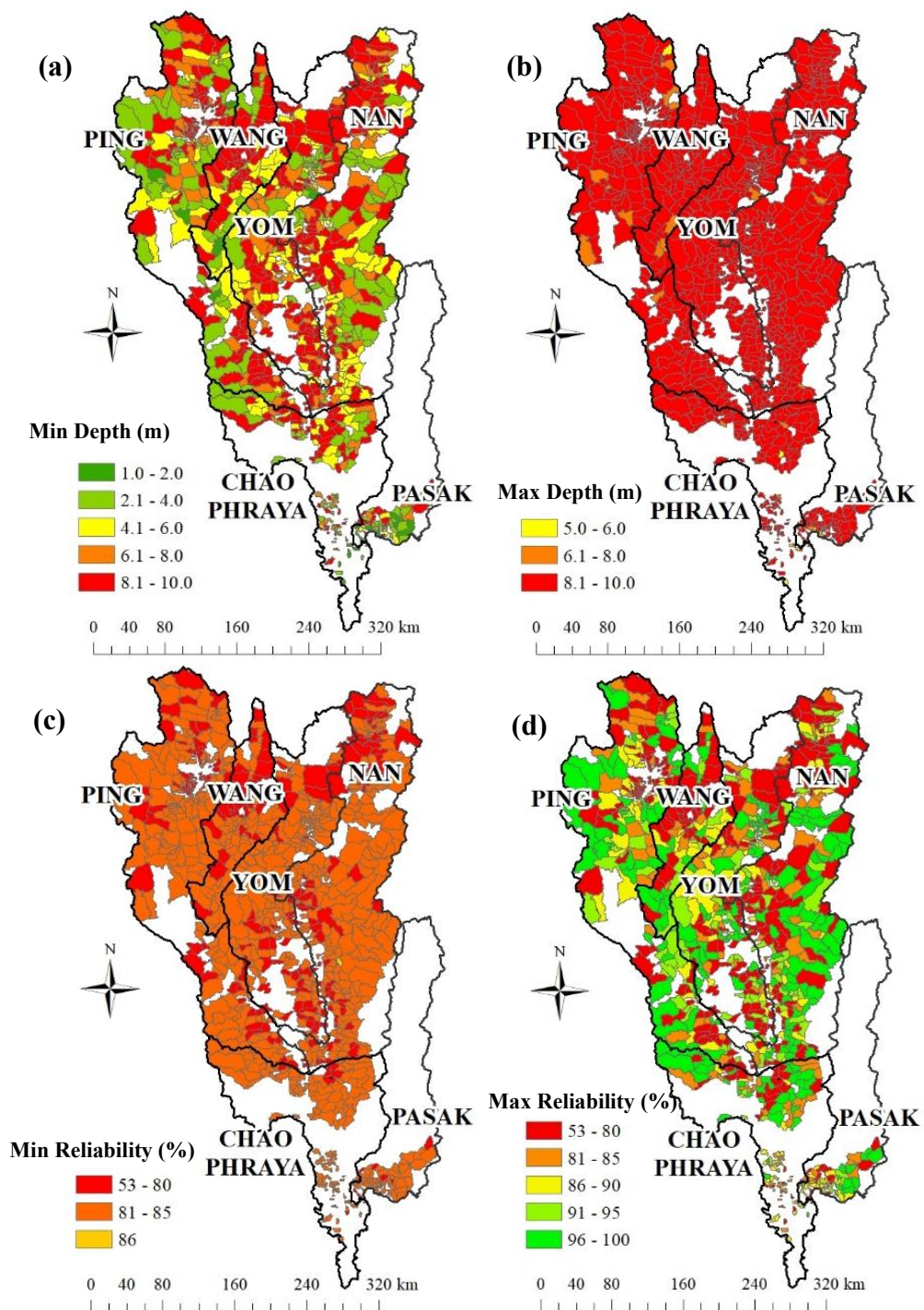


Figure 5.7 Suitable pond depths of the private ponds in the boundary of sub-district, **(a)** minimum and **(b)** maximum values in meters and the reliabilities in percentage related to **(c)** minimum and **(d)** maximum pond depths

5.4.1.3 Future Ponds

The 2,024 units of future ponds were simulated in order to find proper pond designs for changes in various pond depths and areas within the boundaries of the sub-district. At high reliabilities, the minimum and maximum pond capacities in which identify the depths and areas have shown in Figure 5.8.

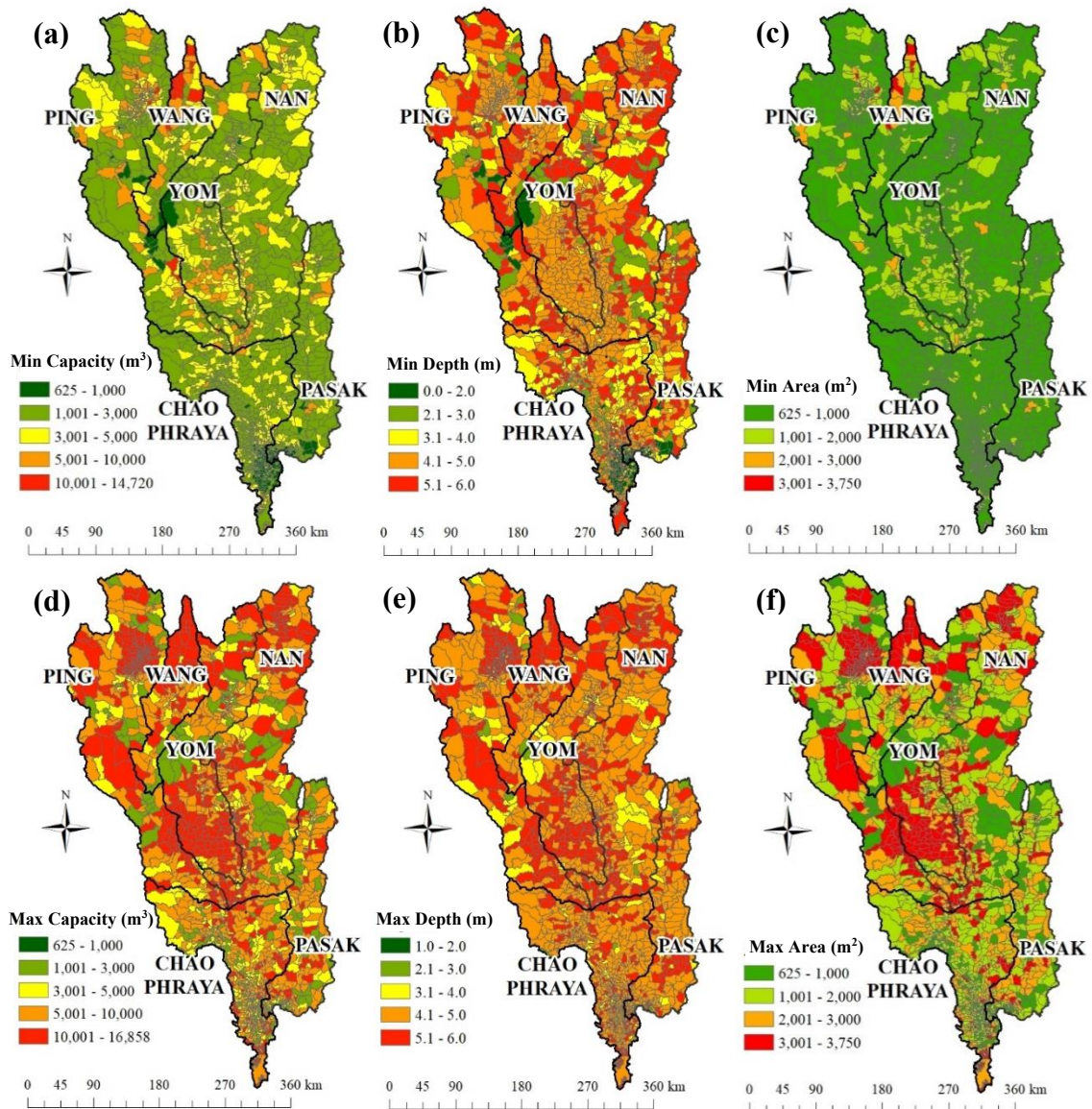


Figure 5.8 Suitable pond designs of future ponds in the boundary of sub-district, (a) minimum capacities (m^3) with (b) depth (m) and (c) area (m^2); and, (d) maximum capacities (m^3) with (e) depth (m) and (f) area (m^2)

In the CPRB, the minimum sizes have resulted in the range between 1,000 and 3,000 cubic meters (Figure 5.8(a)). These ponds could identify various depths from 2 to 5 m. Regards to the maximum capacities, the ponds at deeper than 4 meters are about 91% of CPRB area as shown in Figure 5.8(e). Half of all sub-districts can be constructed within 625 to 2,000 m² of pond areas (Figure 5.8(f)). Particularly, the middle part of the basin should have more than 3,000 m² of pond area due to the annual rainfall above 2,500 mm, excepting the mid-stream of Ping River Basin where the annual rainfall is 500 to 1,500 mm. In total, the appropriate capacities (Figure 5.8(a)) are higher than 5,000 m³, excepting some sub-districts where the annual rainfall is consistency in the range of 1,500 to 2,000 mm.

5.4.2 Estimating Numbers of Future Ponds

With assuming that dry seasonal water requirement is highest in a year, the numbers of future ponds were estimated for each sub-district with consideration of the reconstruction of existing ponds. In the model, the existing public and private on-farm ponds were presumed to be reconstructed where the capacity of pond is smaller than its simulated capacity. About 88% of existing private ponds and 46-63% of existing public ponds were determined to use their simulated capacities from the previous results, as shown in Figure 5.9.

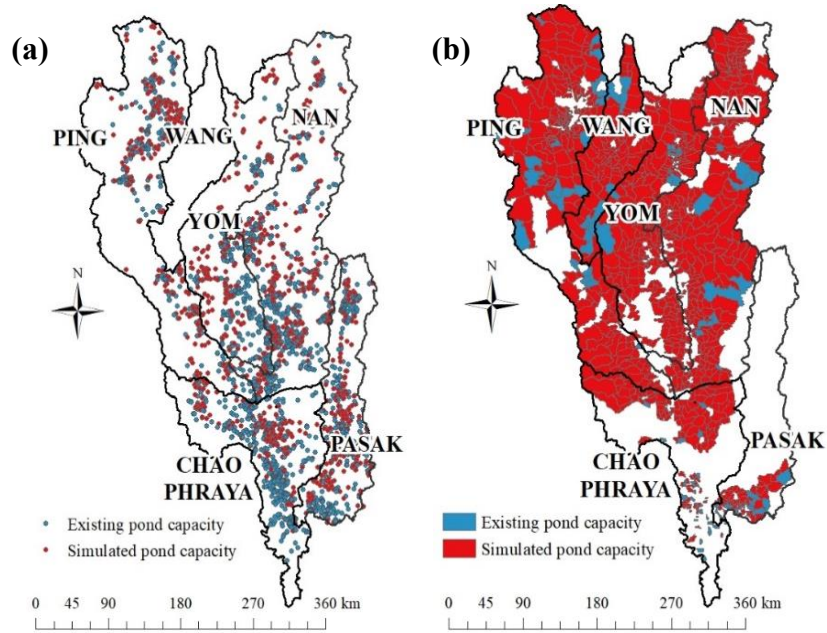


Figure 5.9 Determinations of pond locations of (a) public ponds and (b) private ponds

Since 45 ensemble members, in which each member contains 40 years of future climate data, were input in the model, the number of future ponds in a sub-district often changes depending on the calculation of insufficient water requirements in each climate ensemble member. Due to the various water requirements from different climate datasets, future ponds using their maximum and minimum pond capacities are estimated to be constructed for the lowest and highest values in Figure 5.10.

In the estimation through the maximum and minimum capacities, it clearly shows that new pond construction is undesirable at most areas of the Lower CPRB and lower part of Nan River Basin in which the number of future ponds is equal to zero (blue colour in Figure 5.10). It causes that the areas have been completely built irrigation systems (*e.g.*, dam operations, irrigations, and detention ponds) to support water demands. The number of future ponds, constructed with the maximum capacity of pond, is generally smaller than building the minimum capacity in each sub-district. Accordingly, it shows different

numbers between the results of maximum and minimum capacities at the Upper and Mid CPRB.

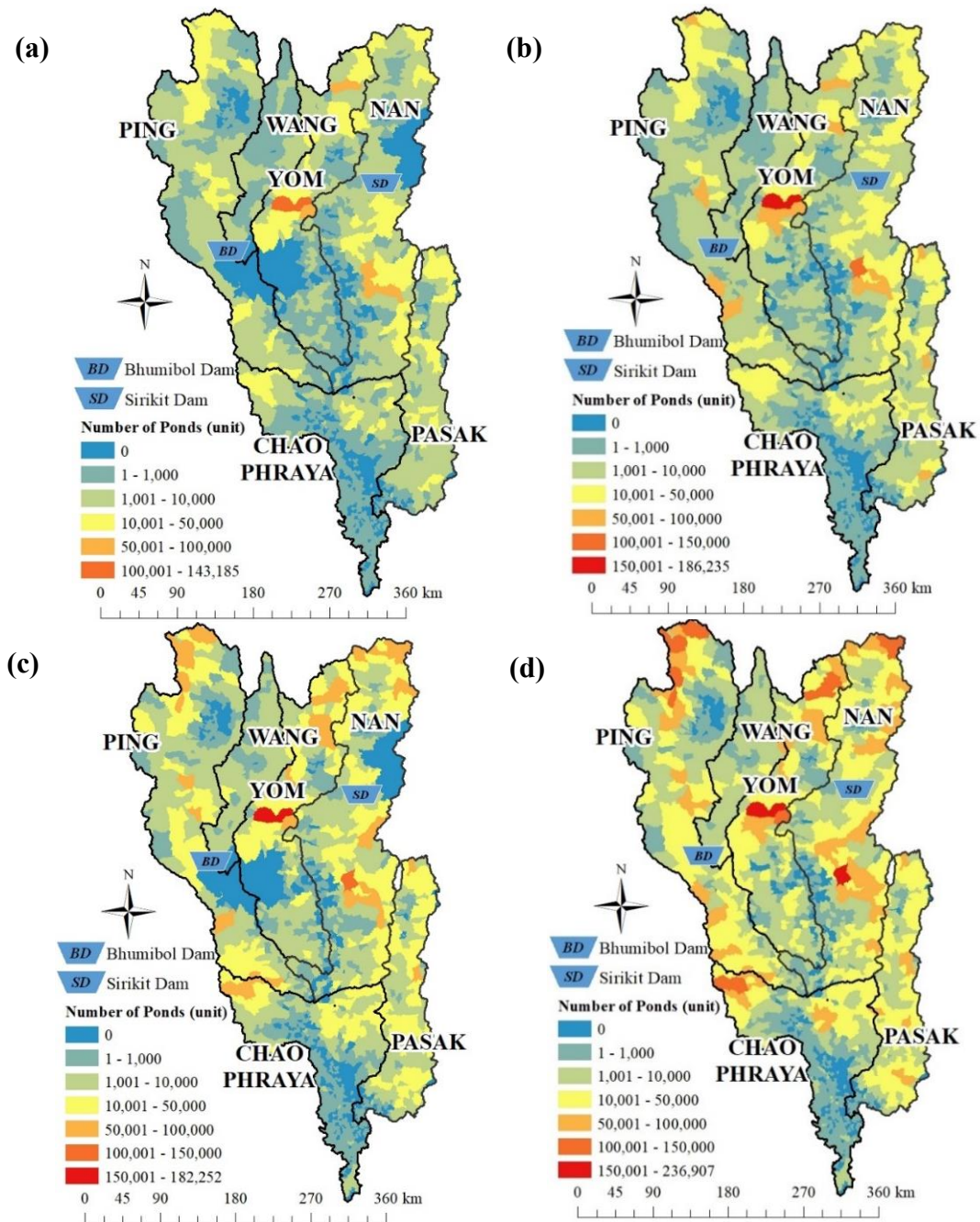


Figure 5.10 Maximum pond capacities estimated for (a) the lowest numbers and (b) the highest numbers of future ponds, and minimum pond capacities estimated for (c) the lowest numbers and (d) the highest numbers of future ponds

For the results of maximum capacities, less than 1,000 units of future ponds (Figure 5.10a) are required to construct and close to 10,000 units (Figure 5.10b) are optional consideration for future construction plans in the upper part of the basin. At the same areas for minimum pond capacities, over 1,000 units (Figure 5.10c) are desired to capture future water demand, and about 10,000-50,000 units (Figure 5.10d) are unrestricted the construction depending on the benefits in each area. Particularly, more than 50,000 units are necessitated in some sub-districts located in the upper part (orange colour in Figures 5.10c and 5.10d) due to deficiency of irrigation systems and high crop water requirements. In middle parts of Ping River and Nan River Basins (blue colour in Figures 5.10a and 5.10c), the results of lowest numbers of future ponds, although both capacities have confirmed that new pond constructions are not needed due to the locations of Bhumibol Dam, the Sirikit Dam and other irrigation projects.

Regards to the large numbers of future ponds (red colour in Figure 5.10), over 143,000 units of future ponds have resulted in constructing in some sub-districts. The huge pond numbers are caused by the results: small pond sizes (1,130-1,345 m² of pond capacity) are recommended for new pond construction, as the water demands of the areas are approximately 100 million cubic meters in average and 230 million cubic meters during the dry seasons. Areas contribute more than 50% of agriculture areas where perennial, orchard and horticulture are main vegetation requiring high water supply during the dry season.

5.4.3 Economic Analysis for Optimizing Pond Numbers

As indicated above, the numbers of future ponds, depending on several factors, *e.g.*, existing irrigation systems, crop water requirement, hydrological condition, and

characteristics of soils, are different in each sub-district. However, government budgets are usually limited to support the projects of water management on a year-by-year basis. The cost-benefit ratio is an assessment to choose which sub-districts should be constructed the new ponds at the priority. The benefits have been estimated by increasing agricultural productions, and the investments for future pond constructions and existing pond reconstructions are included to the costs. The cost-benefit ratio at which the values are higher than 1 means that the benefits at the sub-district overcome the total net cost of construction of the ponds.

In overall viewpoint for the CPRB, the results of the cost-benefit analysis found that construction of maximum pond capacities through the highest and lowest numbers of future ponds could get more benefits than the investment of minimum pond capacities as shown in Figure 5.11. The cost-benefit ratios are generally between 1 and 10. The constructions of maximum pond capacity could decrease investment costs as compared with the minimum pond capacity (Figures 5.11a and 5.11c). Since the lowest numbers of the future ponds through both maximum and minimum capacities could earn great benefits, the cost-benefit ratios are from 100 to 28,336, at the mid Ping and Yom River Basin and upper part of Nan River Basin. However, the ratios with lower values than 1 are deserved in the downstream of the Nan River and Lower CPRB, because there are currently effective irrigation systems in operation. The increasing number of future ponds may not increase agricultural productions in the areas.

Constructions of maximum pond capacities using the highest numbers of future ponds, identified by red colour in Figure 5.11b, could have resulted in a deficit in some dry year due to over-sufficient pond construction in considering crop water requirements. As a similar reason for the construction of the highest number of minimum pond capacities,

Figure 5.11d, a large number of small-scale ponds could spend higher investment cost than constructing a smaller number of larger-scale ponds. Consequently, the constructing maximum pond capacities with the lowest numbers of future ponds could gain more benefits at which the cost-benefit ratios at a higher value than 1 could confirm for 1,734 sub-districts, about 85%. These results would encourage decision-makers in order to plan future water management budgets.

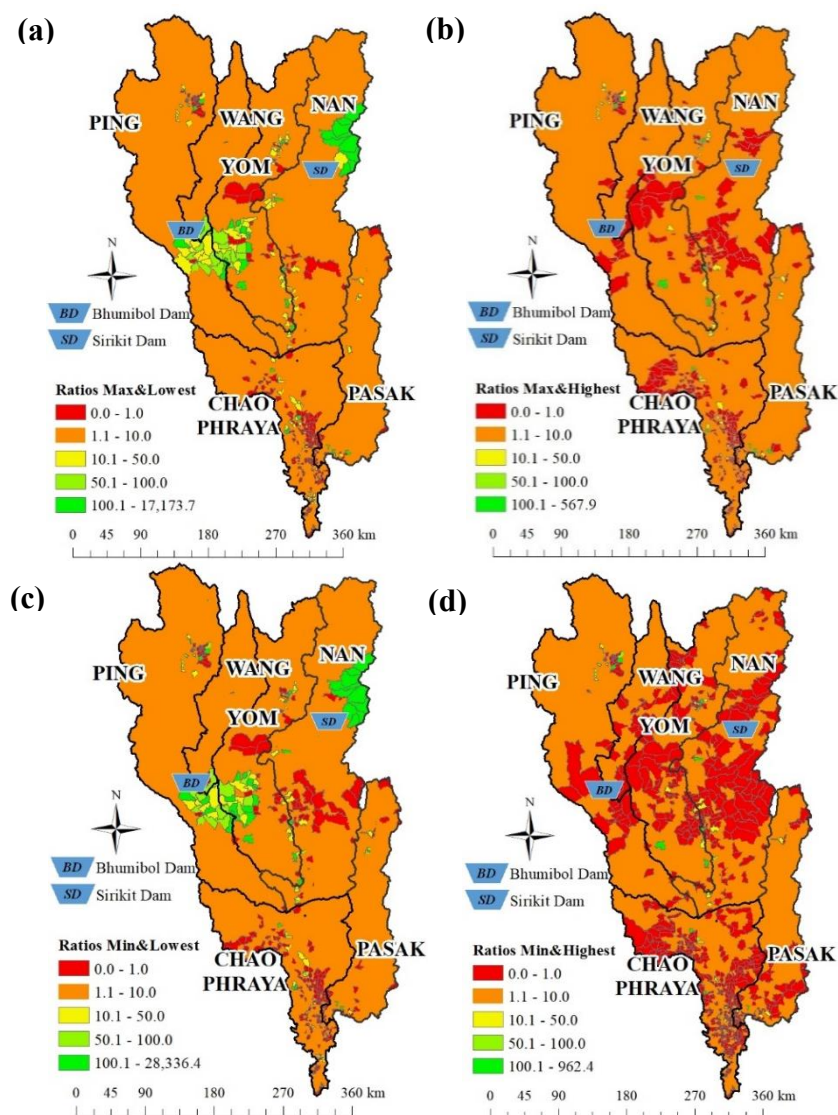


Figure 5.11 Cost-Benefit Ratios using maximum pond capacities estimated (a) the lowest and (b) the highest numbers of future ponds, and minimum pond capacities estimated (c) the lowest and (d) the highest numbers of future ponds

5.5 Summary

The modelling of the pond in combination with the water requirements model and water budget model was constructed in this chapter. Operational rules of the pond have been developed for the purpose of the operating pond, monthly water demands, and protection against floods and droughts. Three pond classifications (public, private and future ponds) were included in the models under which flood control rules commanded to maintain 50% of capacity for public ponds and 20% of capacity for private and future ponds at the beginning of the rainy season.

With a view to optimizing pond capacity considering long-term impacts of climate change, 45 ensemble members of post-processing d4PDF outputs, including 40 years of future climate data, were used to simulate daily pond water levels. Reliability is an assessment to determine appropriate pond designs for public, private, and future ponds. As the results of public ponds at higher than 80% of reliability, appropriate pond ratios of capacity/area are 1-4 meters at floodplain areas, particularly the middle part of the CPRB and Lower CPRB. In mountainous areas, a 10-meter pond depth is required due to the high amount of runoffs and flood occurrences. Moreover, existing private ponds have resulted in the suitable capacities in the ranges of 500-3,250 m³ of minimum capacity and 1,800-3,250 m³ of maximum capacity. It also mentioned that 8-10 meters of private ponds with 625 m³ of pond area should be reconstructed in the CPRB. Due to insufficient water to support agriculture, proper capacities for future ponds in each sub-district have been investigated. For the minimum capacity of the pond, future ponds should be built in the capacity range of 1,000-3,000 m³ with a depth range of 2-4 m. Maximum pond capacities

over 5,000 m³ with a depth of more than 4 m are suggested to be proper designs to protect future overflows.

In order to determine numbers of future ponds, insufficient water requirements, irrigation areas, and existing ponds were involved in the estimation. The results clearly showed that the construction of new ponds in the Lower CPRB and downstream of Nan River is undesirable, because of several irrigation projects. Regards to maximum pond capacities, most of the sub-districts in the Upper CPRB, except for irrigation areas and reservoir locations are recommended to construct 1,000 units of future ponds in case of the lowest number. And 10,000 units are optional consideration for future construction plans to meet future water demands. In addition, the economic model has been used to optimize the numbers of future ponds with maximum and minimum pond capacities using cost-benefit ratios. From the cost-benefit analysis, the maximum pond capacities through the lowest numbers of future ponds could get more benefits than minimum pond capacities.

This chapter has suggested a high number of future ponds constructing in the basin that would change runoffs and river discharges. The use of agricultural ponds to manage watershed is an important challenge for the protections of floods and droughts. Great protection against flooding in ponds connected with flood control in the watershed is evaluated in Chapter 7.

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Chapter 6

Application of Adaptive Neuro-Fuzzy Inference System (ANFIS) for Reservoir Operations

6.1 Introduction

Large-scale reservoirs play an essential role in effective water management. Since mis-operation can create multiple negative impacts, an overview of the water discharge is required with taking into account several variables, *e.g.*, available water in dams, water demand from the downstream, and unsystematic hydrological situations. During different times and hydrological characteristics, the dams were operated differently between dry and wet seasons. In the wet season, high inflow, low water demand, flood protections and saving water for next dry season are important factors regulating how dams should release water. On the other hand, distributing water depending on the water demands and using the available water in the dams to mitigate droughts is a challenge during the dry season.

Due to the complicated criteria, it is recommended to use computing techniques such as Fuzzy logic, Adaptive Neuro-Fuzzy Inference System (ANFIS), and Artificial Neural Network (ANN) to predict the water discharge in the future (Mehta and Jain, 2009). The techniques have their pros and cons. The ANN has difficulties in constructing a suitable training algorithm. Fuzzy logic shows good performance in handling uncertainty, non-linear and noisy data (Jothiprakash and Magar, 2012). However, expert knowledge is required to design fuzzy logic rules in order to construct fuzzy modelling (Jang, 1993).

To overcome this issue, the Neuro-Fuzzy System gets more popular due to the use of the neural network to learn algorithm and the fuzzy system to match input variables associated with output(s) (Fullér, 2000; Chang and Chang, 2006).

By using the Adaptive Neuro-Fuzzy Inference System (ANFIS), the possibility to tune the inputs in the ANFIS is a key to improve the model performance. In order to simulate reservoir water discharge and storage, two algorithms have been considered: a simulation-based algorithm and an optimization-based algorithm. The simulation-based algorithm requires observed information. Schemes have been introduced to use storage capacity, inflow and downstream water demand as input variables (Hanasaki *et al.*, 2006; Coerver *et al.*, 2018). Additionally, for the optimization-based algorithm extreme future inflows, rainfalls and water demands are required in order to decide optimal water discharge and effective reservoir operations (Loucks and Beek, 2017; Coerver *et al.*, 2018).

Because of the benefits of the Neuro-Fuzzy system, we have considered using the ANFIS in this research so that the actual dam operation criteria could be formulated through fuzzy rules. During the construction of ANFIS models, two difficulties exist: which form of membership functions (MFs) is appropriate and how many MFs are required (Gaweda, 2006; Coerver *et al.*, 2018). In the field of the water resources and reservoir operations, limited explanations on how to overcome those questions are provided. Therefore, optimal ANFIS model performances for the Bhumibol and Sirikit Dams are obtained by three research aims: (1) to maximize the ANFIS model performance by determining the appropriate form and the numbers of membership functions (MFs), (2) to explore the relationship between the complexity of input variables

(inflow, storage, rainfall, water demand, and additional set-up) and output (reservoir releases), and (3) to predict reservoir water releases for the future.

6.2 Theories and Principles

6.2.1 Fuzzy Logic System

In fuzzy logic, multiple variable inputs generate a single output or multiple outputs at different time intervals through stipulate input-output pairs. In order to create fuzzy inference output, four procedures (Fuzzification, Inference, Composition, and Defuzzification) contribute to the Fuzzy Inference Systems (FIS).

Fuzzification is a step to identify membership functions (MFs) and membership degrees (MD) in each input variable, as it could be represented by Equation 6.1 (Zimmermann, 2001).

$$A = \{(x, \mu_A(A)), x \in X, \mu_A(A) \in [0,1] \} \quad (6.1)$$

A is the membership function of X where $\mu_A(A)$ is the member degree of x values between 0 and 1. Every membership function (MF) has to identify: (1) forms of membership functions such as triangular, trapezium, Gaussian, B-spline, sigmoid, *etc.*, and (2) membership degrees that define values at points of the membership function shape as considering statistical data of its variable.

The inference is the second step by using the “IF-THEN” principle on the fuzzy logic operations. The “IF” is premised explanations of input variables, and the “THEN” is consequently determined output inferences. From the premised part, the combination of membership degrees could calculate firing strength (weight) of each rule (Chaowiwat, 2012).

Output variables from each fuzzy rule are combined to a single consequent in the third step of the fuzzy inference processes based on relations between the “IF-THEN” rules and actual output. Two fuzzy inference systems, Mamdani and Takagi Sugeno, have different algorithms in the calculation of the combination step. In Mamdani type, the output(s) is related by the minimum operator. Consequent(s) in Takagi Sugeno type is generated by functions of inputs (Gaweda, 2006). Consequently, the key difference is linear or constant for output membership functions (Mehta and Jain, 2009). Finally, the defuzzification is a reversed fuzzification process to generate output results.

6.2.2 Neuro-Fuzzy System

Regarding the abovementioned advantages of Fuzzy logic, however, two difficulties in order to construct fuzzy modelling have been discussed (Jang, 1993). First, the expert knowledge and recorded operation rules are required to transform into fuzzy rules for the premises (Mehta and Jain, 2009). Secondly, the way how users could determine membership functions (MFs) in terms of their values and shapes is a significant approach to maximize modelling performance. The Neuro-Fuzzy System is designed to resolve the difficulty of “IF-THEN” rule’s construction by getting advantages of fuzzy logic and neural network in a single structure. Consequently, the Neuro-Fuzzy System uses the neural network to learn algorithms and use the fuzzy system to capture input variables linked with output(s) (Chang and Chang, 2006). Four processes (Fuzzification, Firing Strength, Consequences, and Aggregation) are provided with five layers in the ANFIS (Chang and Chang, 2006; Coerver *et al.*, 2018) as follows:

1. After the input of numbers and shapes of membership functions, the membership value is determined in the fuzzification step:

$$O_{1,i} = \mu_{A_i}(x) \quad (6.2)$$

Where A_i is a linguistic label (small, medium, or high) of the input variable i , and $\mu_{A_i}(x)$ is a value of its membership function (MF) as defined by the MF's shape. A trapezoidal membership function is given for an example in Equation 6.3.

$$\mu(x) = \frac{1}{1 + \left[\left(\frac{x-c_i}{a_i} \right)^2 \right]^{b_i}} \quad (6.3a)$$

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c \leq x \leq d \\ 0, & d \leq x \end{cases} \quad (6.3b)$$

Or by the alternatively in Equation 6.3c.

$$\mu(x) = \max \left(\min \left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c} \right), 0 \right) \quad (6.3c)$$

In Equation 6.3, a, b, c and d are the premise parameters to determine its shape of membership function (Gaweda, 2006).

2. The firing strength step is to combine all MFs values from the input variables.

$$O_{2,i} = \omega_i = \mu_{A_i}(x) \times \mu_{B_k}(y) \quad (6.4)$$

As $\mu_{B_k}(y)$ is a membership value of the linguistic label B_k of input y .

3. The firing strengths of all nodes are calculated by a normalized firing strength ($\bar{\omega}_i$).

$$O_{3,i} = \bar{\omega}_i = \frac{\omega_i}{\sum_{i=1}^n \omega_i} \quad (6.5)$$

In Equation 6.5, n is the total number of fuzzy rules.

4. The consequence is estimated in each rule through the relationship between input variables and output with using the least-squares estimator as follows:

$$f_i = p_i x + q_i y + r_i \quad (6.6)$$

In Equation 6.6, p_i , q_i and r_i are consequence parameters which can be adjusted during a training process. Then, the consequence for each rule and the normalized firing strength are combined in the consequence nodes to generate output.

$$O_{4,i} = \bar{w}_i \times f_i = \bar{w}_i(p_i x + q_i y + r_i) \quad (6.7)$$

5. The overall outputs from the fourth layer are combined as a final output.

$$O_{5,i} = \sum_{i=1}^N (\bar{w}_i \times f_i) \quad (6.8)$$

The training and checking processes are time-consuming in construction which is a disadvantage of ANFIS (Chang and Chang, 2006). Moreover, the noise of data could not be represented during the training process. Thus, a validation process is needed to check the overfitting of data (Papilinski, 2005).

6.3 Methodology

6.3.1 Data

In order to construct the ANFIS model of reservoir operation, four variables (inflow, rainfall, storage and water demand) are basic inputs to generate the dam water discharge at the daily time interval. The daily reservoir inflow and rainfall are gained from observed data of the years 2000-2012 collected by Electricity Generating Authority of Thailand (EGAT) and Thai Meteorological Department (TMD), respectively. The daily water demand of Bhumibol Dam and Sirikit Dam in the boundaries of their irrigation areas are calculated by the Water Requirements Model in Chapter 5.

For the preparation of future climate data, the Database for Policy Decision-Making for Future Climate Change (d4PDF) is prepared for three ensembles (MI, MP and MR) of two periods: 2051-2070 and 2091-2110. The d4PDF rainfall data are corrected by the

developed bias correction method in Chapter 4. The daily reservoir inflow at upper parts of Bhumibol Dam and Sirikit Dam has been simulated by using Hydrological Simulation Program-Fortran (HSPF) in Chapter 3. The storage is calculated by the water balance equation, in which the evaporation was calculated by the maximum and minimum temperatures of d4PDF data by Hamon method (Martel *et al.*, 2018).

6.3.2 ANFIS Model Developments

In order to construct ANFIS models of reservoir water release for Bhumibol and Sirikit Dams, training and checking processes are required. The four basic inputs were separated in two periods: the years 2005-2012, which involve extreme floods and droughts, for the training; and the years 2000-2004 for the checking process.

6.3.2.1 Dam Operation Policy

Due to the limitations of capacity, maximum water release of a reservoir and downstream river capacity; the dam operation policy was recommended to be done with the simulations of the ANFIS models (Mehta and Jain, 2009). In the models, the current water release and reservoir storage were inputs to calculate the storage at the next time interval by a general reservoir water balance equation (Equation 6.9).

$$S_{t+1} = S_t + Q_t + R_t - O_t - E_t \quad (6.9)$$

The storage at the next time interval (S_{t+1}) is calculated by the inflow (Q_t), the rainfall (R_t), the evaporation (E_t), the storage at the current time interval (S_t) and the released water (O_t) (Maidment, 1993). In Equation 6.9, the released water (O_t) estimated by the ANFIS model states that the amount of water in general depends on the settings of the membership functions (MFs). However, the simulated water release can be outside of

a range between maximum and minimum water releases because of noises. Therefore, the water releases of Bhumibol and Sirikit Dams were commanded to follow three operation rules (Equation 6.10) during the simulation as follows:

Firstly, the water release (O_t) should not be less than 0 m³/s. If the simulated water release is less than 0 m³/s, the release is set to be 50 m³/s as the minimum reservoir water release for Bhumibol and Sirikit Dams in Equation 6.10a.

$$O_t < 0 \text{ m}^3/\text{s}, \text{ then } O_t = 50 \text{ m}^3/\text{s} \quad (6.10a)$$

If the storage at the next time interval is greater than the maximum reservoir's capacity (S_{max}), then the water release at the current time interval (O_t) is re-calculated:

$$S_t > S_{max}, \text{ then } O_t = S_t + Q_t + E_t - S_{max} - R_t \quad (6.10b)$$

If the simulated water release (O_t) is greater than 1,200 m³/s, we set up the water release equal to 750 m³/s and 735 m³/s for the Bhumibol and Sirikit Dams, respectively.

$$O_t > 1200 \text{ m}^3/\text{s}, \text{ then } O_t = 750 \text{ m}^3/\text{s} \text{ and } 735 \text{ m}^3/\text{s} \quad (6.10c)$$

This was gained from their maximum water release rate from their construction until 2016.

6.3.2.2 Adjustments of Membership Functions and Additional Setup

Due to the research objective to maximize the model performances for both dams, membership functions (MFs) were considered in the accomplishment of ANFIS models (Fullér R., 2000). Thus, the forms and numbers of MFs were adjusted for four stages, as shown in Figure 6.1.

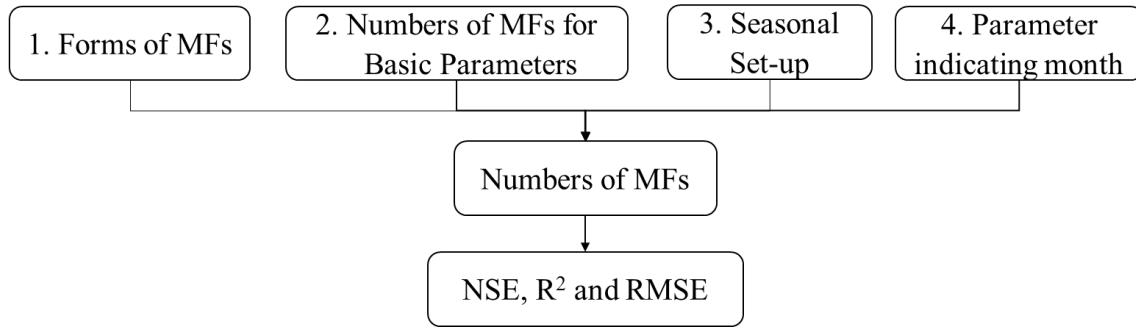


Figure 6.1 Flowchart of adjustments of membership functions

Firstly, the general form of MFs has a high impact on the model performances. However, no evidence and guideline are provided on which form of MFs should be used to set up ANFIS models for dam operations and water resources. In previous researches, the Generalized bell (gbellmf) shaped membership functions have been used without testing (Chang and Chang, 2006; Coerver *et al.*, 2018). There was the question: which form is most appropriate for the use of dam operations. This chapter aim is to investigate a suitable form of MFs by adjusting eight forms: Generalized bell (gbellmf), Gaussian (gaussmf), Gaussian combination (gauss2mf), Difference between two sigmoidal (dsigmf), Product of two sigmoidal (psigmf), Pi (pimf), Triangular (trimf), and Trapezoidal (trapmf) as shown in Figure 6.2.

After selecting the proper form for the MFs, in the second stage, the four basic inputs consisting of inflow, storage, rainfall, and water demand were adjusted to the numbers of MFs. The MFs numbers for inflow and storage were varied from $n = 3$ to $n = 8$, while the numbers between $n = 3$ and $n = 5$ are for rainfall and water demand.

Coerver *et al.* (2018) has mentioned that seasonality improves model performances. In the third stage, the four input variables used in the previous setting were separated into two datasets: the rainy season dataset (May-October) and the dry season dataset (November-April). Then, the seasonal ANFIS models were independently constructed

using both datasets and adjusting various numbers of MFs following the previous range of MFs numbers. The suitable seasonal ANFIS models for dry and rainy seasons were combined to simulate the daily reservoir discharge.

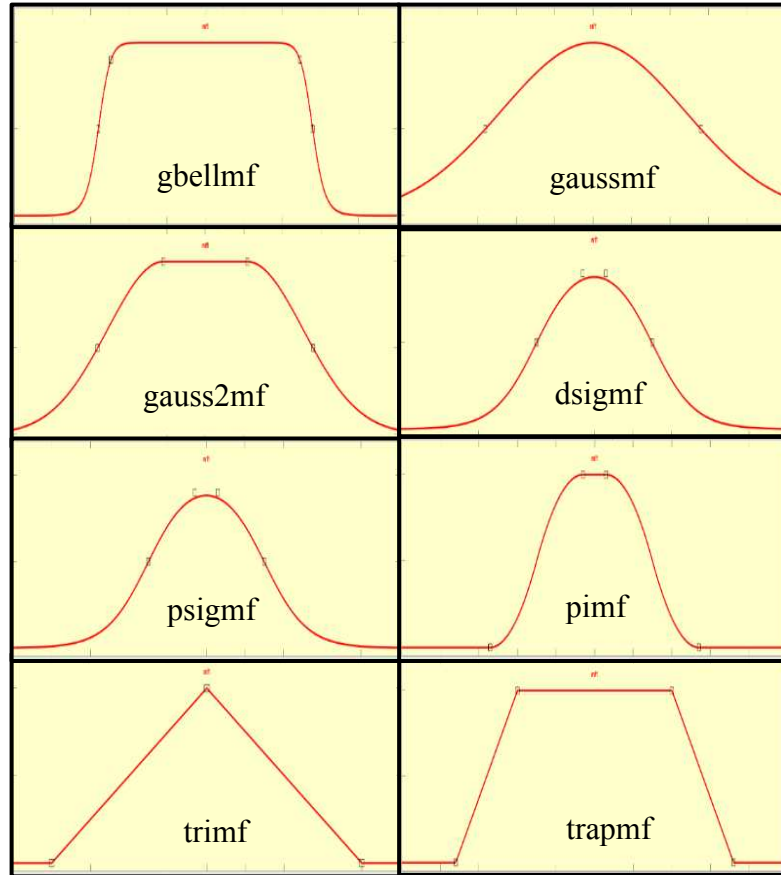


Figure 6.2 Eight forms of membership functions

In order to consider monthly dam operation, the fourth stage is to add an input variable indicating the month. Consequently, five input variables were operated with the selected MFs form in the first stage with adjustable numbers of MFs: from $n = 3$ to $n = 8$ for inflow and storage inputs and from $n = 3$ to $n = 5$ for rainfall, water demand, and month inputs. However, one more input variable increases the time consumed by model construction, especially when the model has more complex membership functions (MFs). Due to this issue, the MFs numbers for the monthly input were compared by their performance at

which the MFs numbers for the other inputs were fixed. At a chosen number of MFs for the monthly input, the numbers of the MFs for the four input variables were randomly changed to construct ANFIS models.

Each model with different numbers of MFs and setup has performed in the training period (2005-2012) and the checking period (2000-2004). Finally, the performance of the simulations is identified by Nash Sutcliffe efficiency (NSE), the coefficient of determination (R^2) and the root mean square error (RMSE).

6.3.2.3 Additional Reservoir Operation for Flood and Drought Protections

Since the ANFIS model only learns the relationship between inputs and output from historical data, the model does not include special dam operations, such as protection of future floods and droughts. In order to achieve an effective reservoir operation, the rainfall downstream of Bhumibol and Sirikit Dams is taken into account in how the dams should release water. The daily rainfall data at ten rain gauge stations, in which three, five, and two gauge stations are located at the downstream of Bhumibol Dam, Sirikit Dam and Lower CPRB, respectively, were estimated by 90th percentile value of the rainfall of each station. The operation rules for flood prevention were designed by considering the timing and the daily release storage ratio (r) from Chapter 3. The daily release storage ratio (r) is calculated by the reservoir release divided with the storage at the current time interval. For the additional operation, the daily release storage ratios (r) of 0.002 and 0.006 were adjusted to be additional water releases between July and August under the conditions: the downstream rainfall is smaller than their 90th percentile values, the storage (S_t) is greater than 8,000 million cubic meters (MCM) for Bhumibol Dam and 6,000 MCM for

Sirikit Dam, and the simulated water release *via* the ANFIS model ($O_{t,ANFIS}$) is lower than 52 MCM as calculated by Equation 6.11a.

$$O_t = O_{t,ANFIS} + r \times S_t \quad \text{for July-August} \quad (6.11a)$$

The daily release storage ratio (r) of 0.001 was commanded for the reservoir release to mitigate downstream overflow during September and October when the simulated water release *via* the ANFIS model ($O_{t,ANFIS}$) is higher than 4.3 MCM, and the rainfall is greater than 90th percentile values as in Equation 6.11b.

$$O_t = 0.001 \times S_t \quad \text{for September-October} \quad (6.11b)$$

Reservoir operation rule for drought mitigation was considered after more than 7 consecutive dry days during dry seasons (November-April) in the Lower CPRB. Because the lowest water volume of 7 MCM is necessary for the Chao Phraya River, Bhumibol and Sirikit Dams were set to release additional water volumes of 14 MCM and 7 MCM, respectively, as in Equation 6.12a and 6.12b.

$$O_t = O_{t,ANFIS} + 14 \text{ MCM} \quad \text{for Bhumibol Dam} \quad (6.12a)$$

$$O_t = O_{t,ANFIS} + 7 \text{ MCM} \quad \text{for Sirikit Dam} \quad (6.12a)$$

In order to choose an appropriate daily release storage ratio (r) for the reservoir operation during July-August, the impacts of the operation using the ratios are examined on river flows. The simulated daily reservoir releases through the ANFIS models and the additional operation were inputs in the hydrological model constructed in Chapter 3. Daily river flows at the Chao Phraya River origin are simulated for three periods: 2000-2010, 2051-2070, and 2091-2100. Then, the changes of river discharges are also represented by the non-exceedance probability of annual maximum daily flow.

After the ANFIS model performance and the appropriate daily release storage ratio (r) were confirmed, the future data are generated by the ANFIS model and the additional reservoir operation for future daily reservoir releases of the three ensembles for the years of 2051-2070 and 2091-2110.

6.4 Results and Discussion

The given three objectives of this chapter, the selection of a suitable form and the numbers of the membership functions (MFs) are discussed through various settings for both Bhumibol and Sirikit Dams. Also, the trends of water releases in the future are investigated.

6.4.1 Selecting a Form of Membership Functions (MFs)

Several researches have reported that the required training and checking processes are time-consuming due to trials and errors (Chang and Chang, 2006; Chaowiwat, 2012; Coerver *et al.*, 2018). In order to save time, the generalized bell-shaped membership function is generally used for reservoir operation without the comparisons of other forms. A few studies have recommended which form of a membership function should be used to generate daily reservoir releases. In order to optimize the model performance, eight forms of membership functions were used during the training process using a similarly observed dataset of the years 2006-2012. The numbers of MFs associated with each input variable were adjusted to $n = 3$ based on linguistic values that are high, medium and low. With regards to the comparison of different forms, Figures 6.3 and 6.4 illustrate model performances *via* the coefficient of determination (R^2) for Bhumibol and Sirikit Dams, respectively.

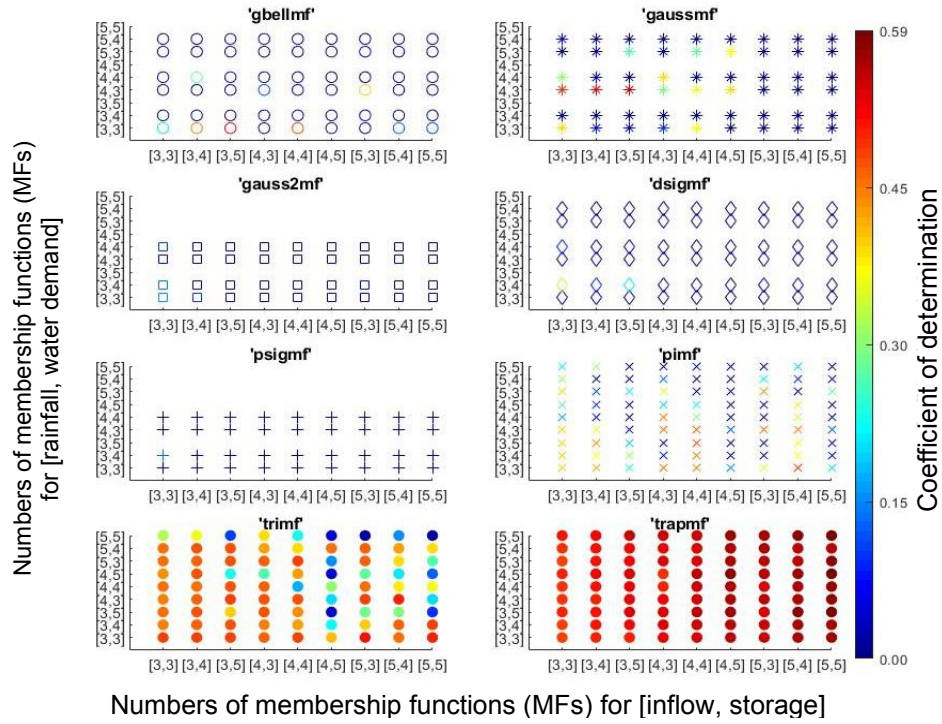


Figure 6.3 Model performance using the coefficient of determination (R^2) for daily reservoir releases of Bhumibol Dam

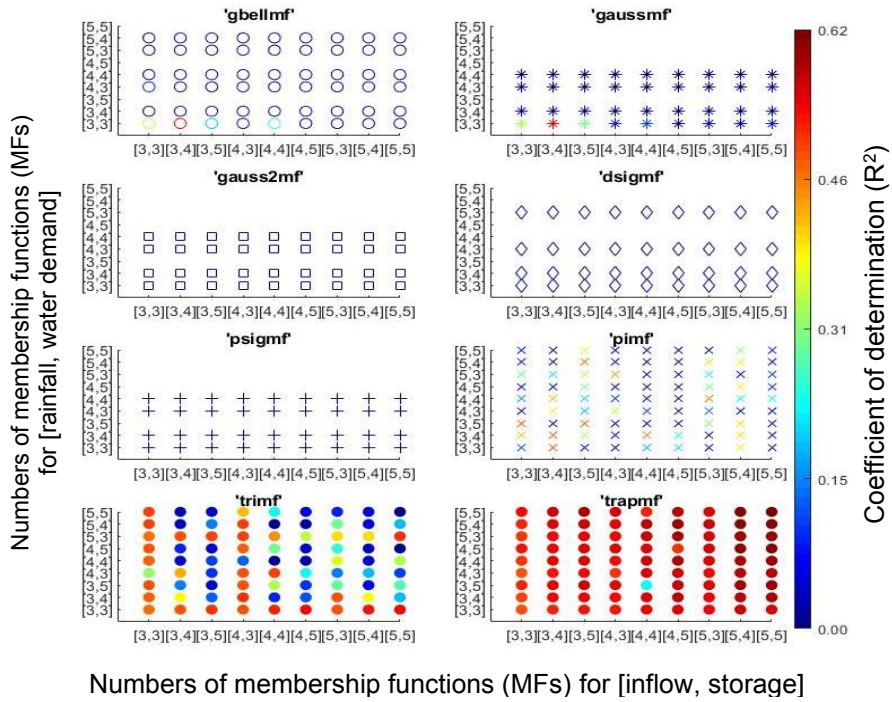


Figure 6.4 Model performance using the coefficient of determination (R^2) for daily reservoir releases of Sirikit Dam

In Figures 6.3 and 6.4, the coefficient of determination (R^2) for daily reservoir releases of both dams is denoted by the colour bar. The dark blue colour indicates unacceptable performance ($R^2 = 0.0$), the red colour for satisfactory performance ($R^2 > 0.5$). The x-axis represents the numbers of MFs for inflow and storage, and the y-axis for rainfall and water demand. Figures 6.3 and 6.4 depict that the trapezoidal-shaped membership function expresses the most satisfactory performance at most numbers of MFs for both dams. The triangular-shaped and the pi-shaped membership functions also indicate an acceptable simulation quality on specific numbers of MFs. Considering the numbers of MFs used for the trapezoidal-shaped form, the coefficient of determination (R^2) obviously increases when the numbers of MFs for inflow and storage as input variables are more complex.

6.4.2 Optimal ANFIS Model Performances

6.4.2.1 Basic Parameters

As mentioned above, the performance of the ANFIS models during the training process shows good performance for the trapezoidal-shaped membership function. In this section, the numbers of MFs in the range between $n = 3$ and $n = 8$ for inputs of inflow and storage and from $n = 3$ to $n = 5$ for rainfall and water demand were varied. The basic four input variables were used to construct ANFIS models for Bhumibol Dam and Sirikit Dam, as shown in Figures 6.5 and 6.6. The Nash Sutcliffe efficiency (NSE) values indicate the model performance of the various MFs numbers during the training (2005-2012) and the checking (2000-2004) processes. In the training process, the NSE values could be increased by adding higher numbers of MFs for inflow and storage inputs.

However, due to more complex MFs numbers for rainfall and water demand, the model performance could not increase.

For the ANFIS models of Bhumibol Dam, the MFs numbers for inflow and storage inputs at $n \geq 6$ could produce satisfactory performances during the training period (NSE > 0.61) in Figure 6.5(a). In the checking process (Figure 6.5(b)) used for validation, the NSE values are generally higher. Particularly, the number of MFs for storage input is more complicated with a value of $n = 7$, these NSE values are however not usable (NSE < 0.19).

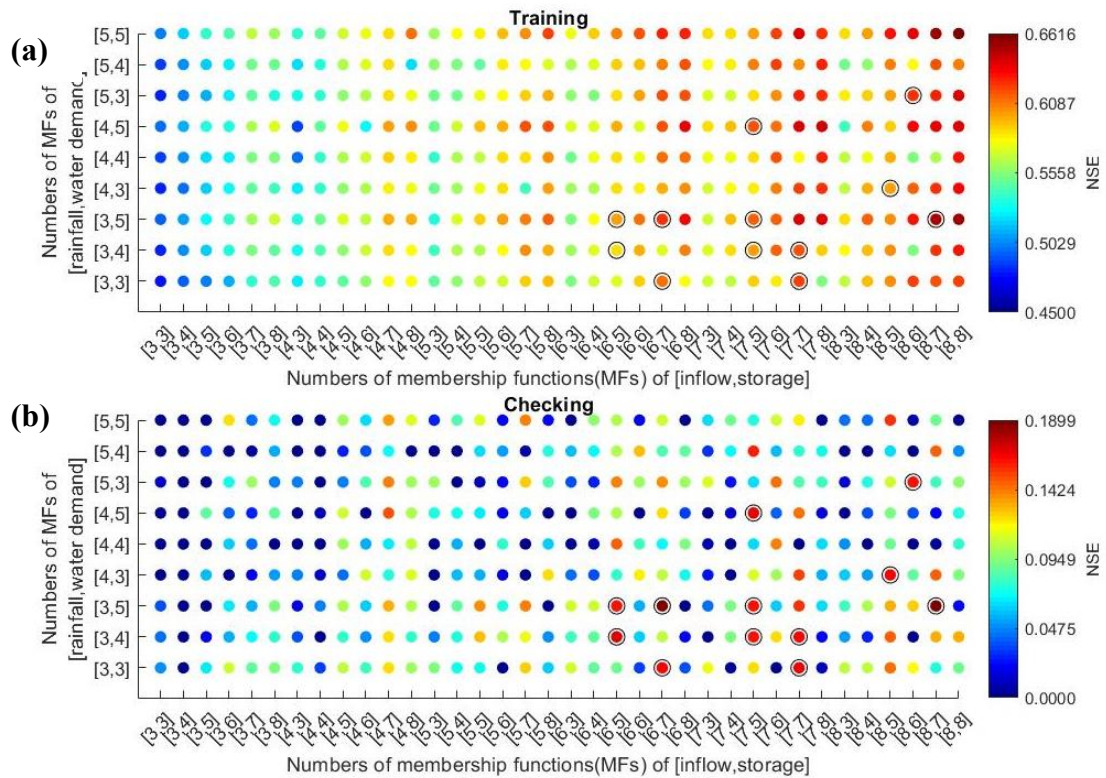


Figure 6.5 Model performance using NSE for daily reservoir releases of Bhumibol Dam: (a) training process (2005-2012) and (b) checking process (2000-2004)

On the other hand, increasing the MFs number for storage input does not increase the NSE values in the checking period for the ANFIS models of the Sirikit Dam. In Figure 6.6b, the MFs for inflow at numbers $n = 3$ and $n = 4$ trend to have better results with NSE

values of the checking process that are more than 0.35. It was found that the reservoir releases of Sirikit dam depend on inflow in priority.

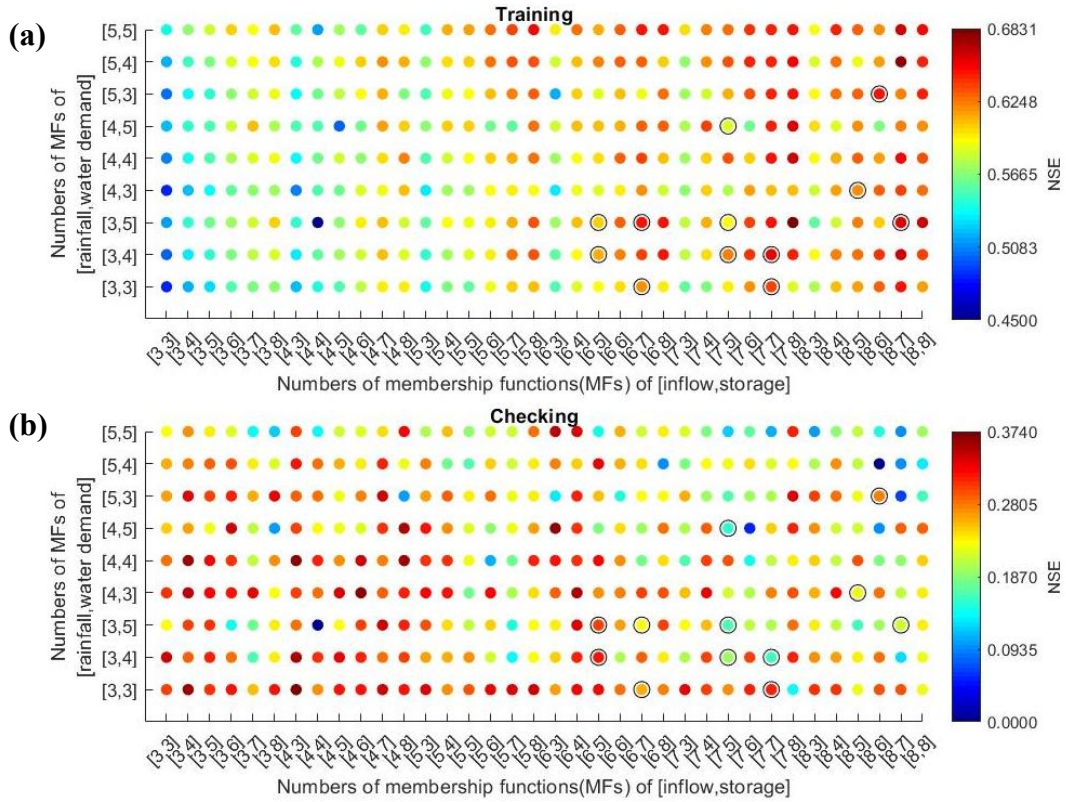


Figure 6.6 Model performance using NSE for daily reservoir releases of Bhumibol Dam: **(a)** Training process (2005-2012) and **(b)** Checking process (2000-2004)

6.4.2.2 Seasonal Set-up

Due to the unacceptable results for the NSE values, we considered to improve the model performance with a seasonality factor. The ANFIS models based on the seasonality were created for the dry season (November-April) and the rainy season (May-October). In a similar model construction approach, the four input variables for the daily reservoir release for Bhumibol Dam were generated by the results of rainy and dry seasonal models as shown in Figures 6.7 and 6.8, respectively. The best results of the training process, showing a satisfactory performance ($NSE > 0.5$), were achieved when the numbers of

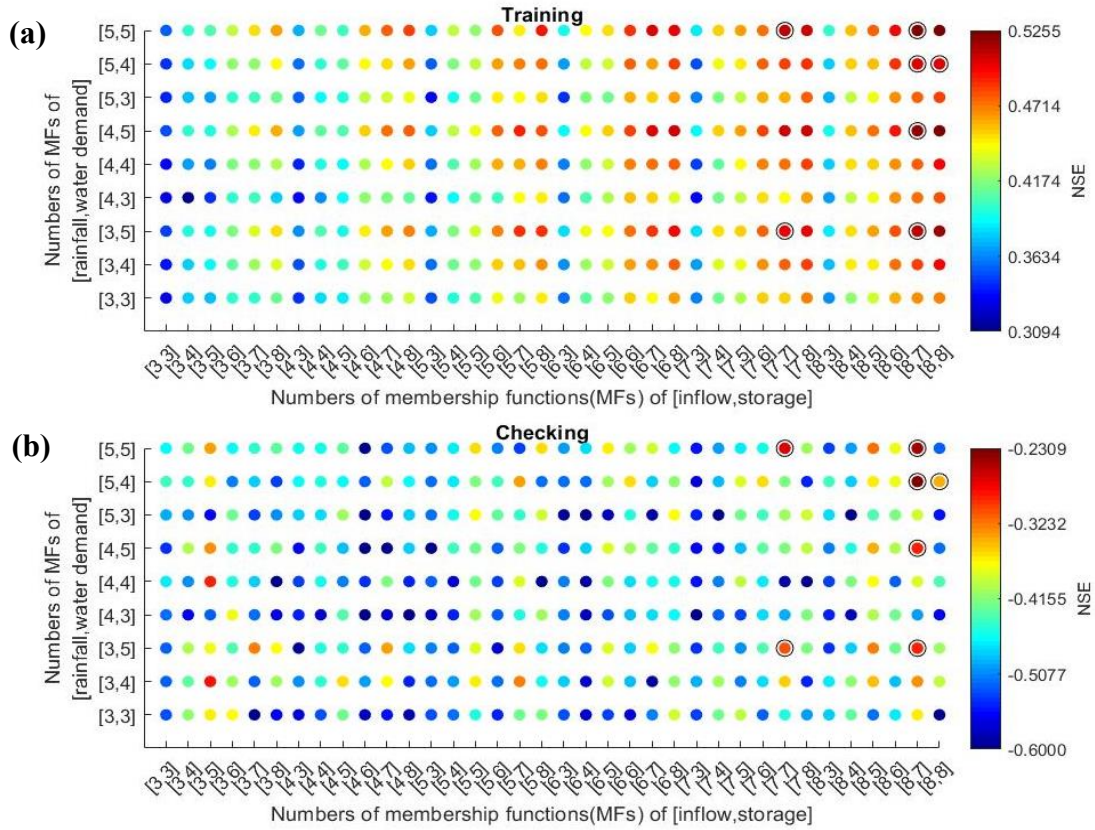


Figure 6.8 Model performances of dry seasonal ANFIS models using Nash Sutcliffe Efficiency (NSE) for (a) training process and (b) checking process

From the previous results, the higher NSE values of the rainy and dry seasonal models (circles in Figures 6.7(b) and 6.8(b)) were combined to simulate the daily reservoir discharges as shown in Figure 6.9. All results of the training process show good performance ($NSE > 0.65$), while the maximum NSE value of the checking process (Figure 6.9(b)) is 0.29. Even if a better performance of the training process is generated, it might not always simulate a better performance of the checking process due to the characteristics and time dependency of data.

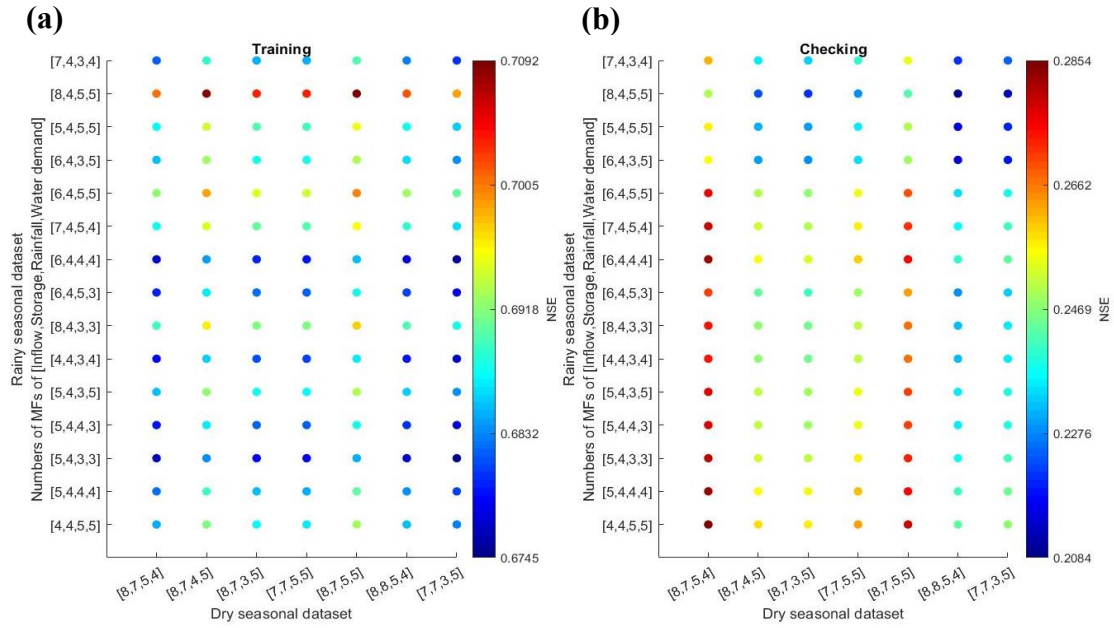


Figure 6.9 Model performances for Bhumibol Dam presented by NSE value using specific MFs numbers between dry (x-axis) and rainy (y-axis) seasonal ANFIS models: **(a)** training process (2005-2012) and **(b)** checking process (2000-2004)

Due to the unsatisfied model performance of the Sirikit Dam in the previous section, the seasonality is also applied in a similar procedure as of the Bhumibol Dam's model construction. The better performance of each seasonal model was selected by NSE values for both training and checking processes. Then, the models from rainy and dry seasonal datasets were combined, as shown in Figure 6.10. Satisfactory performances have been achieved in the training process ($NSE > 0.63$). The best performance was also validated by the checking process. The rainy seasonal ANFIS models mainly affect NSE values. More specifically, the MFs numbers for inflow, storage, rainfall, and water demand inputs at $n = 6, 3, 4$, and 4 , respectively, for the rainy seasonal ANFIS model express the best result ($NSE = 0.46$). In consideration of seasonality, the inputs were divided into rainy and dry datasets. The establishment of two ANFIS models obtained better performances,

because the inputs in the aggregated ANFIS models can match with a higher amount of numbers of fuzzy rules and thus generate a more accurate output.

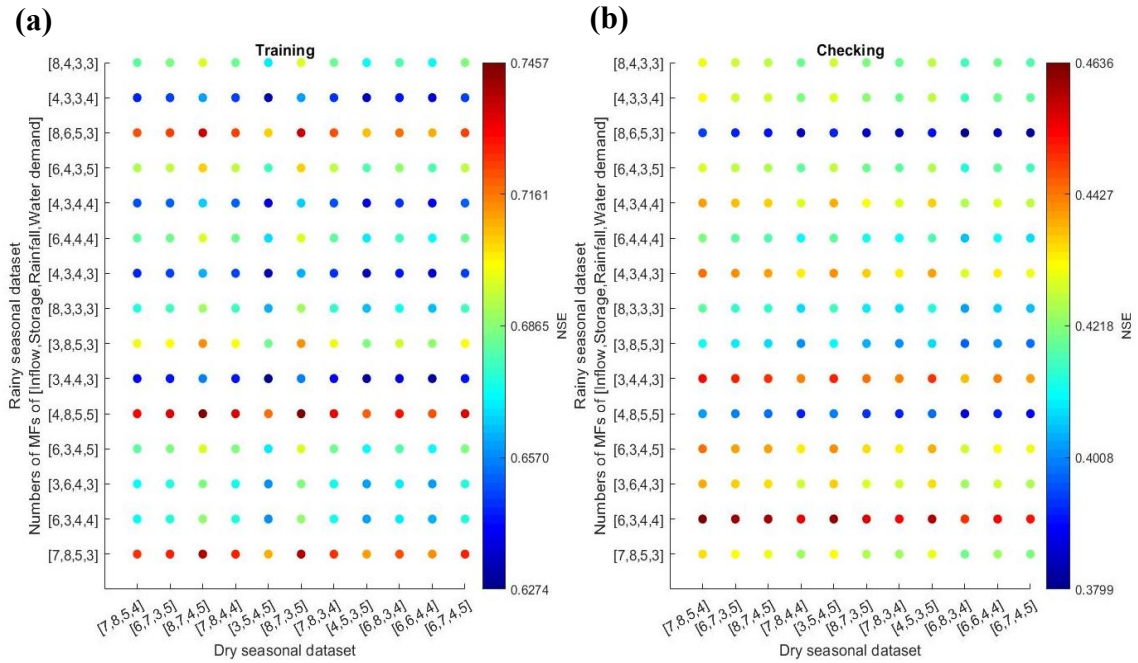


Figure 6.10 Model performances for Sirikit Dam present by NSE value using specific MFs numbers between dry (x-axis) and rainy (y-axis) seasonal ANFIS models: **(a)** training process (2005-2012) and **(b)** checking process (2000-2004)

6.4.2.3 Additional Monthly Input Parameter

Chang and Chang (2006) have mentioned that a disadvantage of the Neuro-Fuzzy system is that the training and checking processes are time-consuming for model construction. In the previous sections, we have constructed numerous ANFIS models to optimize model performance. In there, the NSE value of the checking process was prioritized since the noise of data could not be represented during the training process (Papilinski, 2005). When the training and checking processes were operated, the ANFIS model could select parameters based on the minimum checking data error that is always included during noisy measurements. However, the previous results are not satisfactory

for the NSE values of checking process that are lower than 0.5, even though the model performance of the training process is satisfactory.

A. Bhumibol Dam

In order to improve the model performance, we have considered that the dam operation depends on monthly antecedent effective storage ratios of the Bhumibol Dam. These ratios are changed every year by the Royal Irrigation Department (RID). Due to this, in this section, we added an input to identify the month. In total, five input variables were used to construct ANFIS models with adjusted numbers of MFs. By increasing one input variable, the model construction of each set of membership functions requires more time because its fuzzy system needs to add more fuzzy rules and to tune more premise and consequence parameters from Equations 6.2 to 6.8. According to the limited computer capacity and model running time, the numbers of MFs for monthly input were set from $n = 3$ to $n = 5$, which are compared in Figure 6.11.

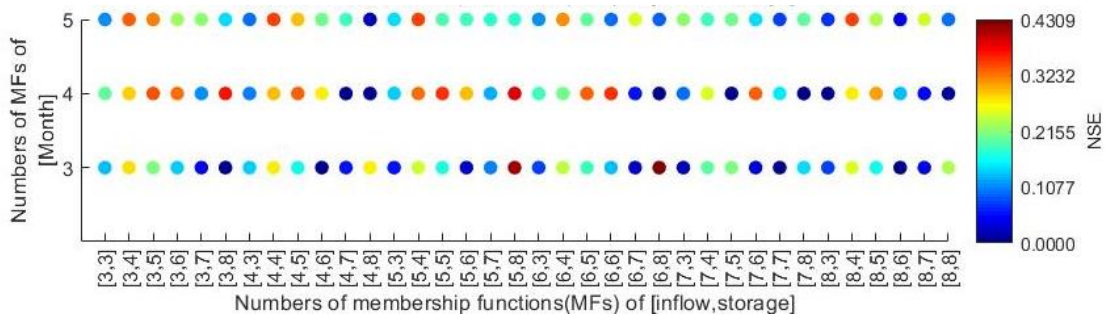


Figure 6.11 Model performances of Bhumibol Dam using Nash Sutcliffe efficiency (NSE) through adjusting an additional input of month for the checking process

Considering the performance of the checking process, the MFs numbers for the monthly input between $n = 3$ and $n = 4$ tend to have a better performance than $n = 5$. Additionally, adjusting the complexity of the MFs numbers for rainfall and water demand inputs is illustrated for the MFs numbers for monthly input at $n = 3$ and $n = 4$ in Figures 6.12 and 6.13, respectively.

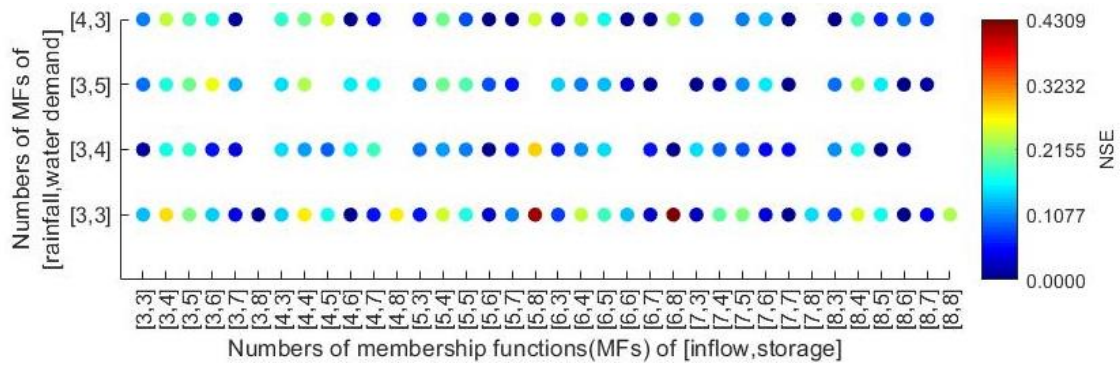


Figure 6.12 Model performances of Bhumibol Dam using Nash Sutcliffe efficiency (NSE) through the MFs number for a monthly input at $n = 3$ for the checking process

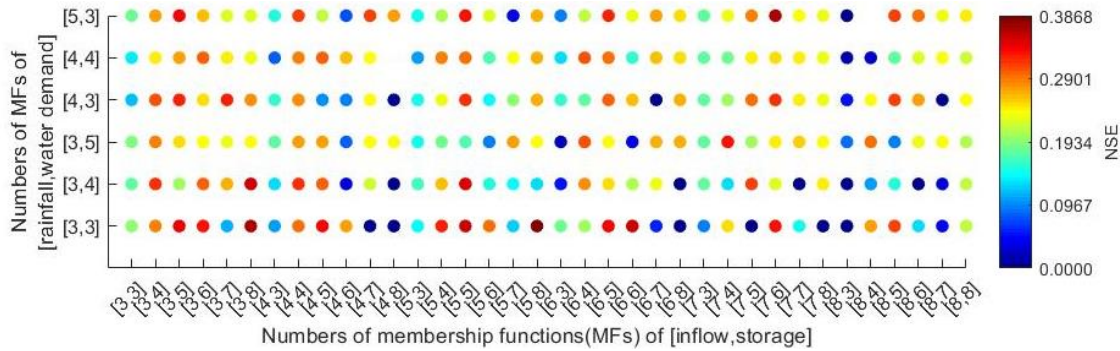


Figure 6.13 Model performances of Bhumibol Dam using Nash Sutcliffe efficiency (NSE) through the MFs number for a monthly input at $n = 4$ for the checking process

The NSE values of the training process could reach higher than 0.7, which expresses a good performance. Also, it can be implied that the MFs number for the storage parameter is the most significant. Through increasing the more complex MFs number for the storage input, particularly at the $n = 8$ during the checking process (Figures 6.12 and

6.13), it was found that the inflow has the second position in affecting the performance. If the MFs number for inflow input is more or less complicated, the model reflects by a lowering performance. Besides, the adjustment of the MFs numbers for rainfall and water demand inputs is not as important as the storage and inflow indicators. When comparing between the seasonal set-up and the additional parameter indicating month for the models of Bhumibol Dam, the month input could improve the maximum NSE value from 0.29 to 0.43. The better performance of the Bhumibol dam's operation is based on the monthly pattern and the increase of fuzzy rules. As the number of inputs is increased, the number of fuzzy rules also increases. By using the four basic parameters, 270 fuzzy rules have been created, while the basic parameters combined with the additional parameter of the month established 540 rules. The increase of fuzzy rules could have additional potential in covering rare cases of dam operation, including flood events. Consequently, the optimize performance of ANFIS model of Bhumibol Dam is 0.43 of NSE value ($R^2 = 0.59$ and $RMSE = 77.64$) when the MFs numbers for inflow, storage, rainfall, water demand, and monthly inputs are $n = 6, 8, 3, 3,$ and 3 , respectively. The optimized performance of the simulated daily reservoir releases is shown in Figure 6.14.

In the training period of the years 2005-2012, the trend of water discharges is similar for observation and simulated output. About 50-400 m^3/s of water discharge during the dry season. Particularly, in 2011 and 2012, more than 400 m^3/s of water was attempted to discharge from the Bhumibol Dam, the highest value since the 2011 flood condition (Figure 6.14(a)). However, the ANFIS system could not capture this special operation since downstream floods are not considered in the model; therefore, the simulated result is underestimated in the training process. In the checking process from the years 2000 to 2004 (Figure 6.14(b)), the daily water releases are generally overestimated. This result

could imply that during the training process the premise and consequence parameters are determined by learning the dam operation pattern. However, the dam operation of Bhumibol Dam is unrestricted. Consequently, the change of MFs numbers and the additional parameter indicating month could improve the model performance but not enough to get good enough results for the daily time-series.

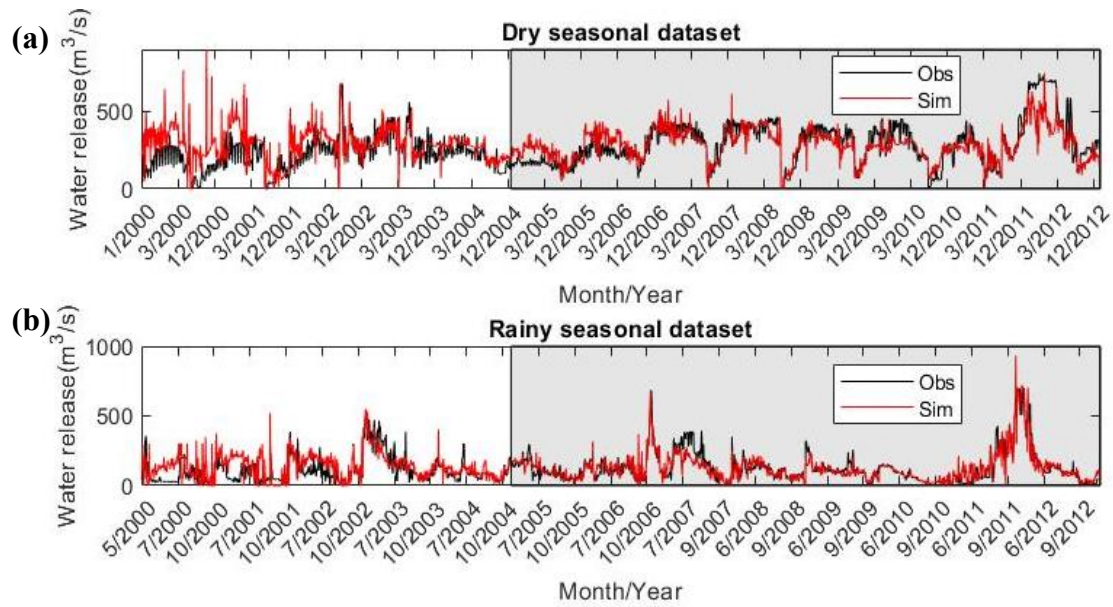


Figure 6.14 Daily reservoir releases of Bhumibol Dam using the optimize model performance in separations of **(a)** dry seasonal dataset and **(b)** rainy seasonal dataset

B. Sirikit Dam

The additional parameter indicating month was also applied to the ANFIS models of the Sirikit Dam's operation. The MFs number for the monthly parameter was varied between $n = 3$ and $n = 5$ in a similar procedure used for the model construction of the Bhumibol Dam. Figure 6.15 illustrates the performance through the setting of five parameters while fixing the MFs numbers for rainfall and water demand inputs at $n = 3$. The MFs of the additional parameter have resulted in the appropriate number of $n = 4$. The adjustment of more complicated numbers for basic inputs is presented in Figure 6.16.

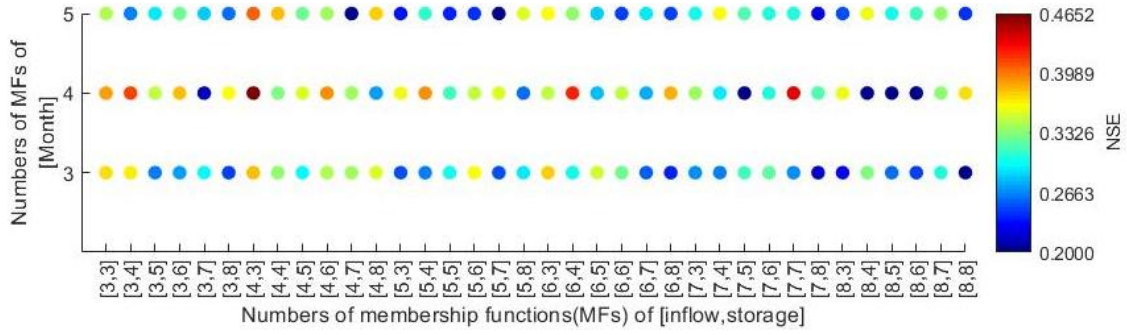


Figure 6.15 Model performances of Sirikit Dam using Nash Sutcliffe efficiency (NSE) through adjusting an additional input of month for the checking process

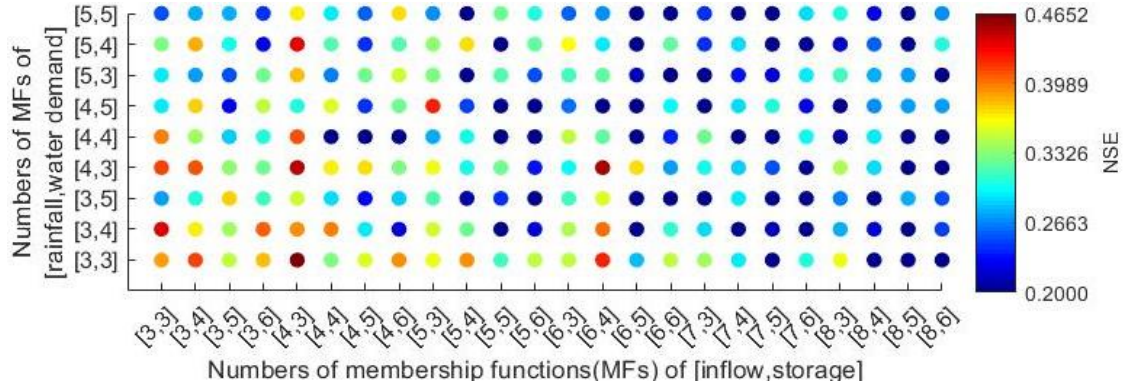


Figure 6.16 Model performances of Sirikit Dam using Nash Sutcliffe efficiency (NSE) through the MFs number for a monthly input at $n = 4$ for the checking processes

In total, the maximum NSE value is 0.47 ($R^2 = 0.50$ and $RMSE = 89.32$) when the MFs numbers for inflow, storage, rainfall, water demand and month inputs are $n = 4, 3, 3, 3$, and 4, respectively (Figure 6.16). From the previous results of the basic parameters, it can also be confirmed that the MFs numbers for inflow and storage parameters at $n = 4$ and $n = 3$, respectively, are suitable for the ANFIS model of the Sirikit Dam. The reduced complexity of the MFs number means that the Sirikit Dam was operated with similar operation patterns year after year. Particularly, the MFs number for storage input at $n = 3$ could be implied in the linguistic label into low, medium and high storages. By adding the input indicating the month, the model performance shows a minimal improvement

when compared with the seasonal condition. Higher complexity of the inputs and the member functions seems to be insufficient in order to obtain good performance for simulating the daily reservoir releases. It is caused by the limitation of the timeframe for the training period. The duration should be extended to include more cases of floods and droughts (Coerver *et al.*, 2018).

Additionally, the daily water releases of the training (2005-2012) and checking (2000-2004) processes are presented for the dry and rainy seasonal datasets, as shown in Figure 6.17. The optimized ANFIS model with five parameters could learn an algorithm of Sirikit's Dam operation since the dam has a similar pattern of water discharge almost every year. Exceptions are the high water discharges of the dry seasons in 2011 and 2012 due to the high water storage after the massive floods in 2011. During the checking process, the optimized ANFIS model could simulate daily water releases, especially the dry season of the normal water years 2002-2004. The simulated water discharges during the rainy season of the year 2001 are fluctuating due to abnormal dam operations such as the sudden release of high water amounts over 500 m³/s.

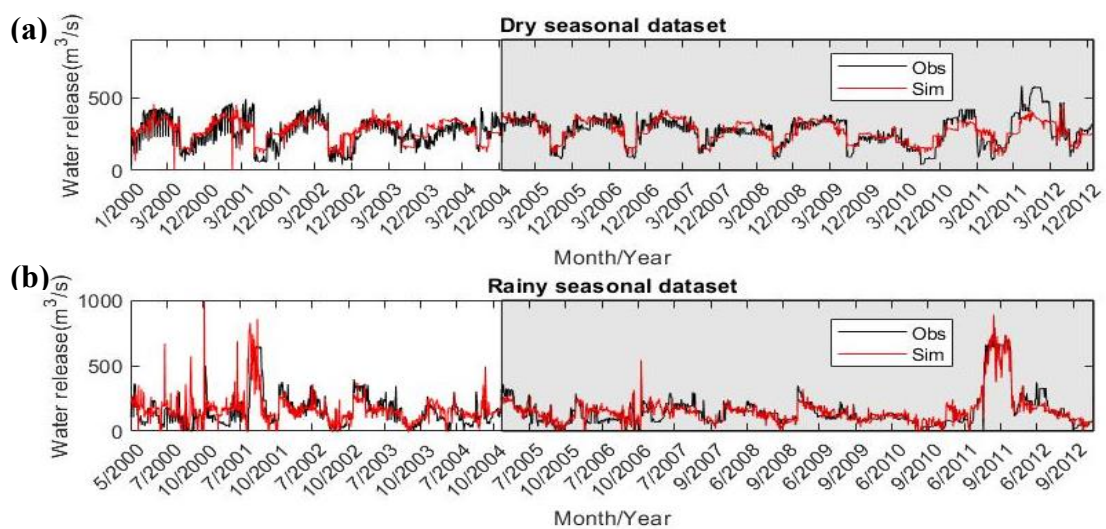


Figure 6.17 Daily reservoir releases using the optimize model performance in separations of **(a)** dry seasonal dataset and **(b)** rainy seasonal dataset

Consequently, the optimized ANFIS models of the Bhumibol Dam and the Sirikit Dam in the training process could not capture the high water releases during the dry season due to the effects of the 2011 floods. The overestimated water releases have been simulated in the checking process, and therefore the NSE values of the checking process are less than 0.5. The special cases of dam operation should be considered in future research, *e.g.*, very high water release during the dry season.

6.4.3 Additional Reservoir Operation

Since the ANFIS models of both dams could not capture the special reservoir operation during the floods in 2011, the timing and the daily release storage ratios (r) were applied for the additional operation. In general, when the annual maximum river flow occurs in September or October, the dam operation in both months in the model is commanded to release the small amount of 0.001 of the current storage as suggested for flood protection in Chapter 3. By releasing the small volume at the end of the rainy season, the reservoirs are required to have bigger storage and release a higher water amount. The daily release storage ratios (r) of 0.002 and 0.006 accordingly were adjusted to increase the water discharge at the mid-rainy season as shown in Figure 6.18. Moreover, the additional operation managed to add an additional water release of about 14 MCM for Bhumibol Dam and 7 MCM for Sirikit Dam during the dry season. Through the setup of the daily release storage ratios, the reservoir water release is slightly higher between July and August, and very high water releases ($> 600 \text{ m}^3/\text{s}$) are dramatically decreased (Figure 6.18(a)). Also, an increase in the water release is shown during the dry season (November-March).

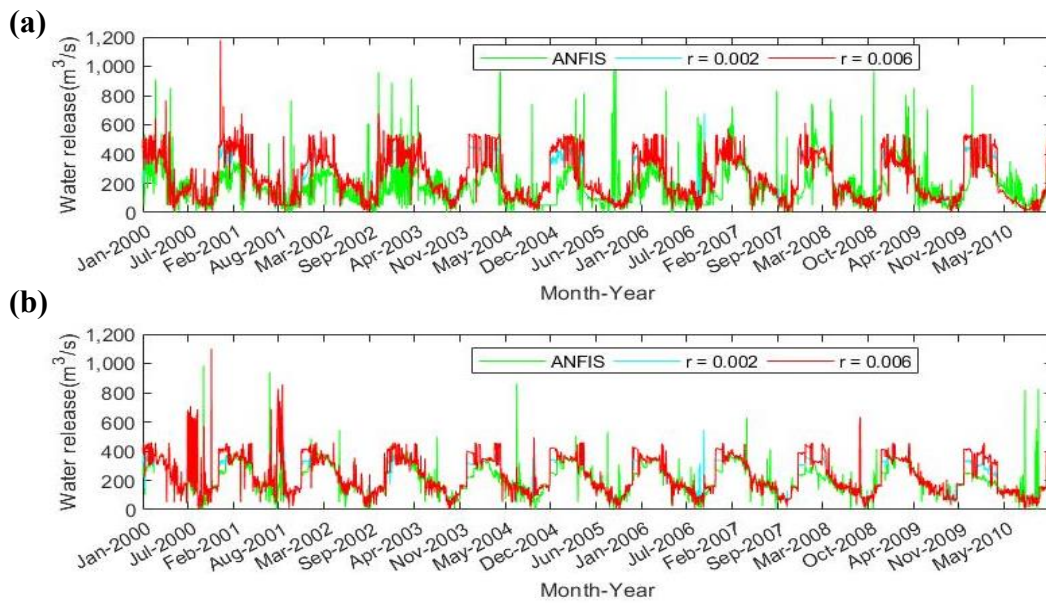


Figure 6.18 Daily reservoir water release (m^3/s) using ANFIS model, daily release storage ratio (r) of 0.002, and the ratio of 0.006 for **(a)** Bhumibol Dam and **(b)** Sirikit Dam

In order to choose the appropriate daily release storage ratio, impacts of both ratios (0.002 and 0.006) were examined on the daily river flow at the origin of the Chao Phraya River as shown in Figure 6.19. The river flow of the period 2000-2010 (Figure 6.19(a)) is slightly increased during the low flow. In contrast, the highest flows are decreased, particularly for the flood peaks in 2002 and 2006.

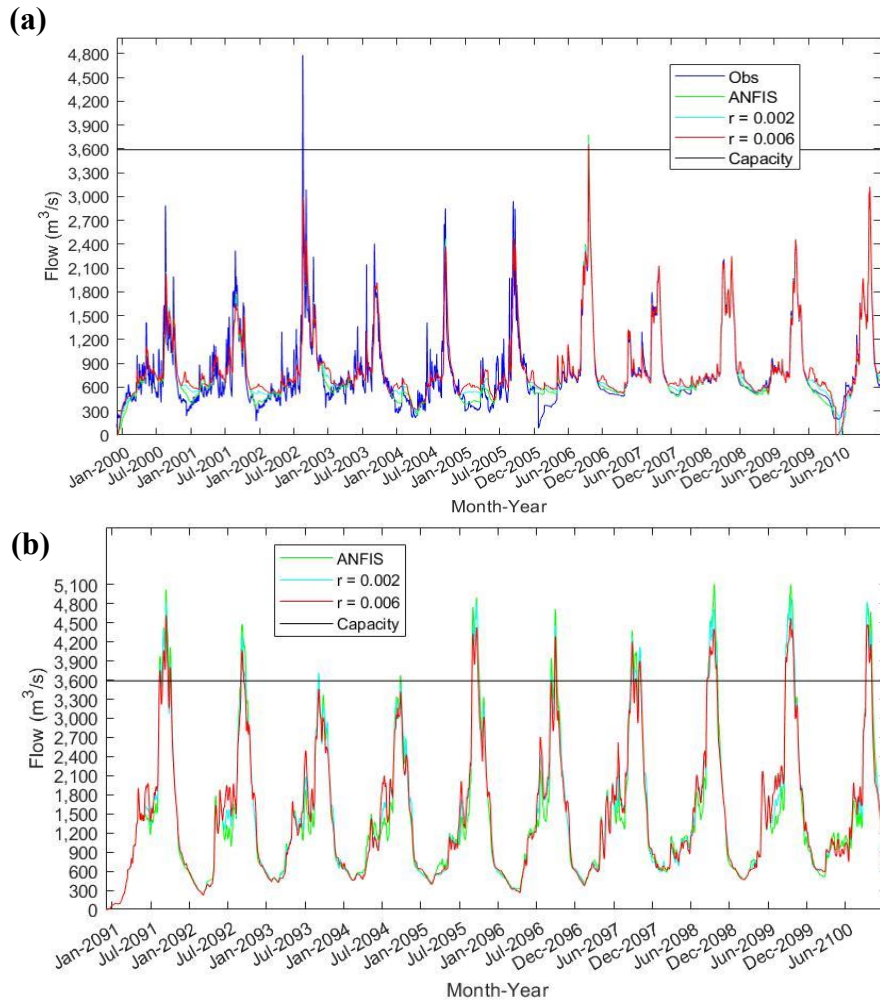


Figure 6.19 Daily river flows at the Chao Phraya River origin by setting ANFIS model, daily release storage ratio (r) of 0.002, and the ratio of 0.006 for two periods: **(a)** 2000-2010 and **(b)** 2091-2100

In future maximum flow, there is a trend of a general increase as shown in Figure 6.19(b). This river flow could be damped out by using the daily release storage ratios of 0.002 and 0.006. Particularly, the highest decrease of the flow peaks is identified by the ratio of 0.006. Moreover, the non-exceedance probability of annual maximum daily river flow using the daily release storage ratio (r) of 0.006 was also confirmed the decreases in extreme flow events as shown in Figure 6.20. When the non-exceedance probability is higher than 0.50, the annual highest flow could be reduced about 500-1,500 m³/s from the

ANFIS model. Consequently, the daily release storage ratio of 0.006 is the best choice to simulate future reservoir water release for flood prevention.

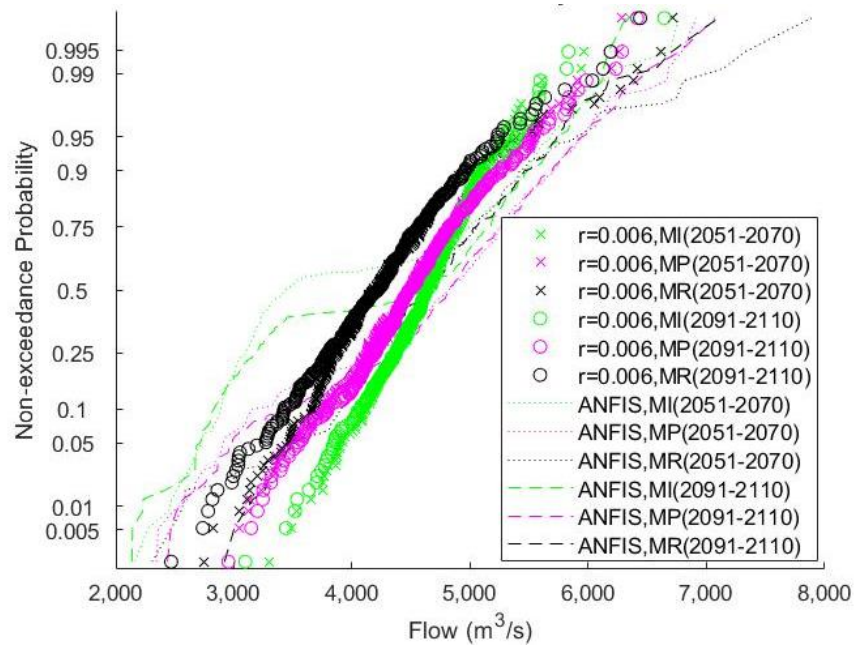


Figure 6.20 Probability of annual maximum daily flow using ANFIS model and daily release storage ratio (r) of 0.006 for three ensembles (MI, MP and MR) of the periods 2051-2070 and 2091-2110 at the Chao Phraya River origin

6.4.4 Trends of Reservoir Water Releases in Future

6.4.4.1 Bhumibol Dam

In the previous results of optimizing the reservoir operation of Bhumibol dam, the five input parameters, including the additional monthly parameter, showed the best performance. The additional reservoir operation is also designed by using the daily release storage ratios (r) for protection against floods and droughts. The 45 members of MI, MP, and MR ensembles of future climate data of the two periods (2051-2070 and 2091-2110) were performed to simulate daily water releases through the optimized ANFIS model of Bhumibol Dam and the additional reservoir operation. Figure 6.21 illustrates the water release trend in the past and future trends of monthly inflow, water release, and storage

using the ANFIS model and the daily release storage ratio (r) of 0.006. Since the ANFIS model has learned a pattern of daily water releases in a short period of the training process, water releases using the ANFIS model express a similar trend with the discharge of the year 2011 (Figure 6.21(a)) when the massive floods occurred. As the experience of misoperation of Bhumibol Dam was blamed after the floods in 2011, the reservoir operation should be improved by releasing more water volume before the highest inflow. While comparing the past and future trends of reservoir releases (Figure 6.21(a)), a more effective reservoir operation is recommended by using the additional reservoir operation with the daily release storage ratio (r) of 0.006. Through the additional reservoir operation ($r = 0.006$), 500-2,000 million cubic meters (MCM) of water is released during the mid-rainy season (Figure 6.21(a)). When the monthly inflow is higher than 1,000 MCM, the water releases decrease. After the peak of monthly inflow of approximately 2,700 MCM, less than 400 MCM of water should be discharged at the end of the rainy season (September to October) for flood prevention. During the dry season (November to April), 700-1,200 MCM water per month is required to meet the water demands and to mitigate the drought on downstream. In the last three months of the rainy season, the Bhumibol Dam could store 3,500-4,000 MCM (26-30% of the reservoir capacity) to support the water demands in the next dry season. When comparing the storage trends (Figure 6.21(b)), the storage *via* the ANFIS model is generally higher than the ratio ($r = 0.006$) and the upper rule curve, especially during the mid-rainy season (July-August).

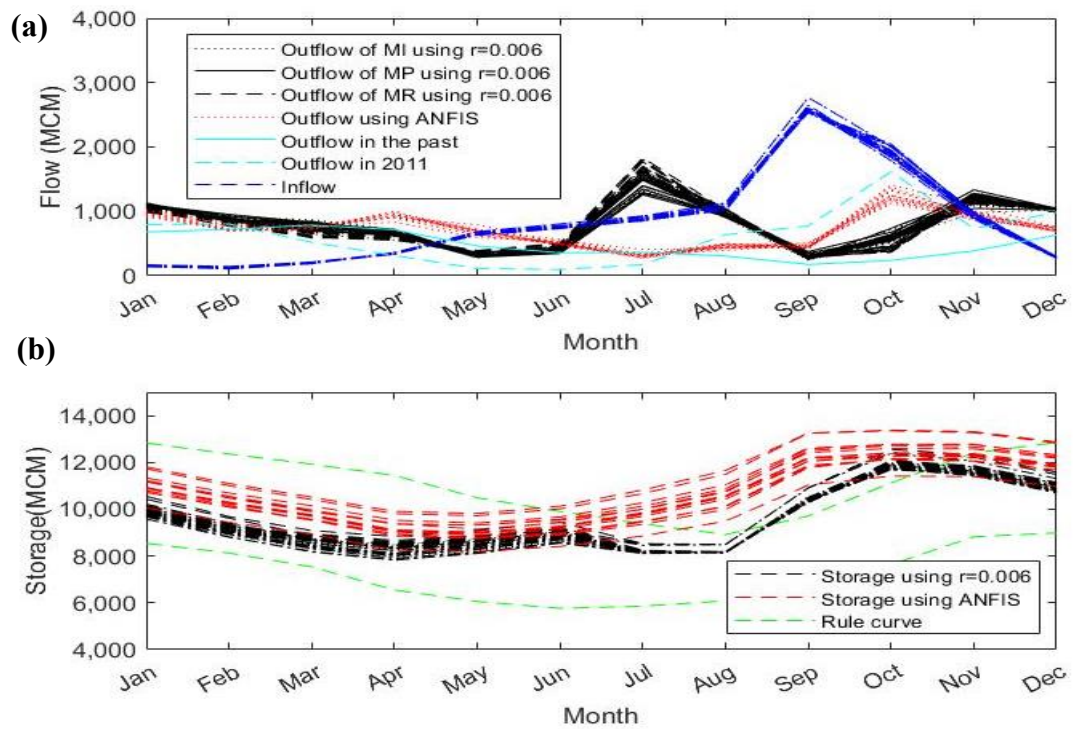


Figure 6.21 Future trends of (a) monthly inflow, reservoir water release and (b) storage for the reservoir operation of Bhumibol Dam

Indeed, the inflows of both rainy and dry seasons are influenced by rainfalls in each climate ensemble member. Lower than 50 MCM per day and 15 MCM per day of inflows are normal ranges of rainy and dry seasons, respectively, as shown in Figure 6.22. However, the maximum inflow leads to 190 MCM per day through MR m102 ensemble member (Figure 6.22(a)) while the 140 MCM per day is the highest inflow *via* the MR m103 ensemble member (Figure 6.22(b)). This hydrological variability affects the reservoir water release as over 70 MCM/day of water should be released during the rainy season (Figures 6.23(a) and 6.23(b)). During the dry season, 20-45 MCM/day of water is generally discharged to meet water demands on downstream, as shown in Figures 6.23(c) and 6.23(d). Particularly, since the maximum inflow of MRm103 ensemble member is

smaller than MRm102, the reservoir discharges more water, approximately 25 MCM/day, through MRm103 (Figure 6.23(d)).

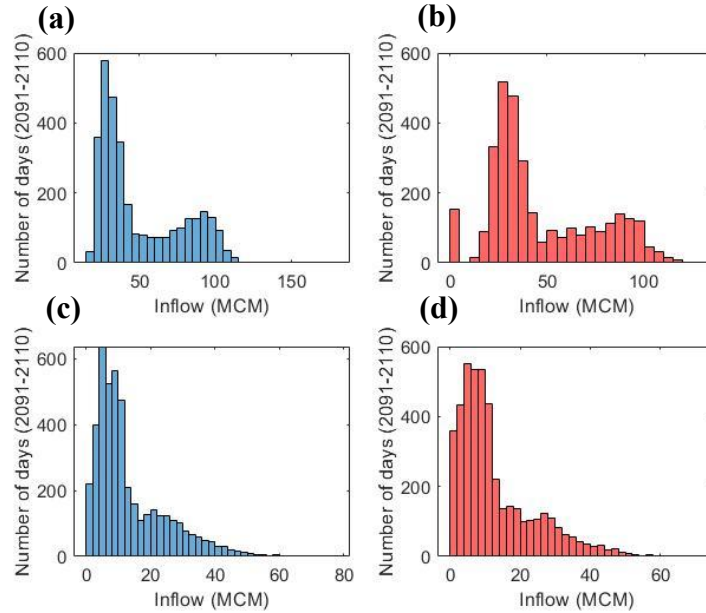


Figure 6.22 Histograms of Bhumibol Dam for daily inflows of the years 2091-2110 during the rainy season using (a) MRm102 and (b) MRm103 ensemble members and during the dry season using (c) MRm102 and (d) MRm103 ensemble members

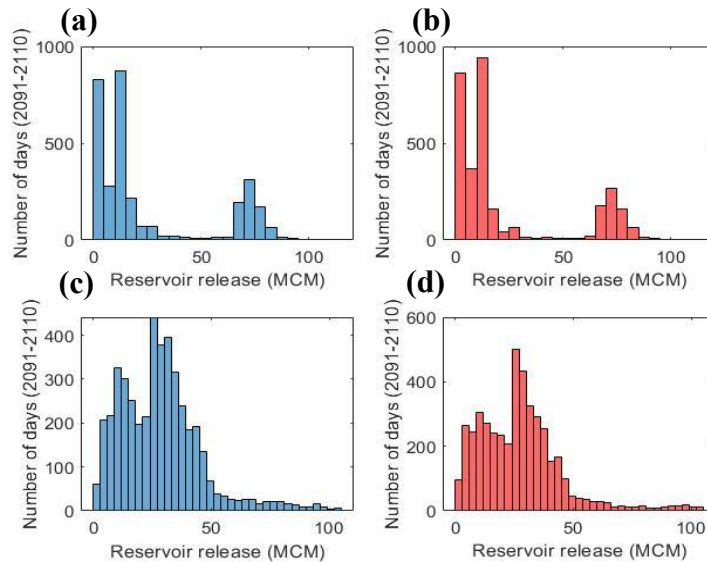


Figure 6.23 Histograms of Bhumibol Dam for reservoir water releases of the years 2091-2110 during the rainy season using (a) MRm102 and (b) MRm103 ensemble members and during the dry season using (c) MRm102 and (d) MRm103 ensemble members

6.4.4.2 Sirikit Dam

The optimize ANFIS model through the five parameters involving the input of month could show the best performance. By applying the model and the additional reservoir operation, future climate data were used to predict the daily reservoir water releases of Sirikit Dam. The trends of monthly inflow, storage, and reservoir water release in the past and future are shown in Figure 6.24. In comparison with the reservoir release trend in the past, the future water discharges using the daily release storage ratio (r) of 0.006 are similar to the operation in 2011 at the mid-rainy season, then the releases are decreased as followed the average water release in the past at the end of the rainy season (Figure 6.24(a)).

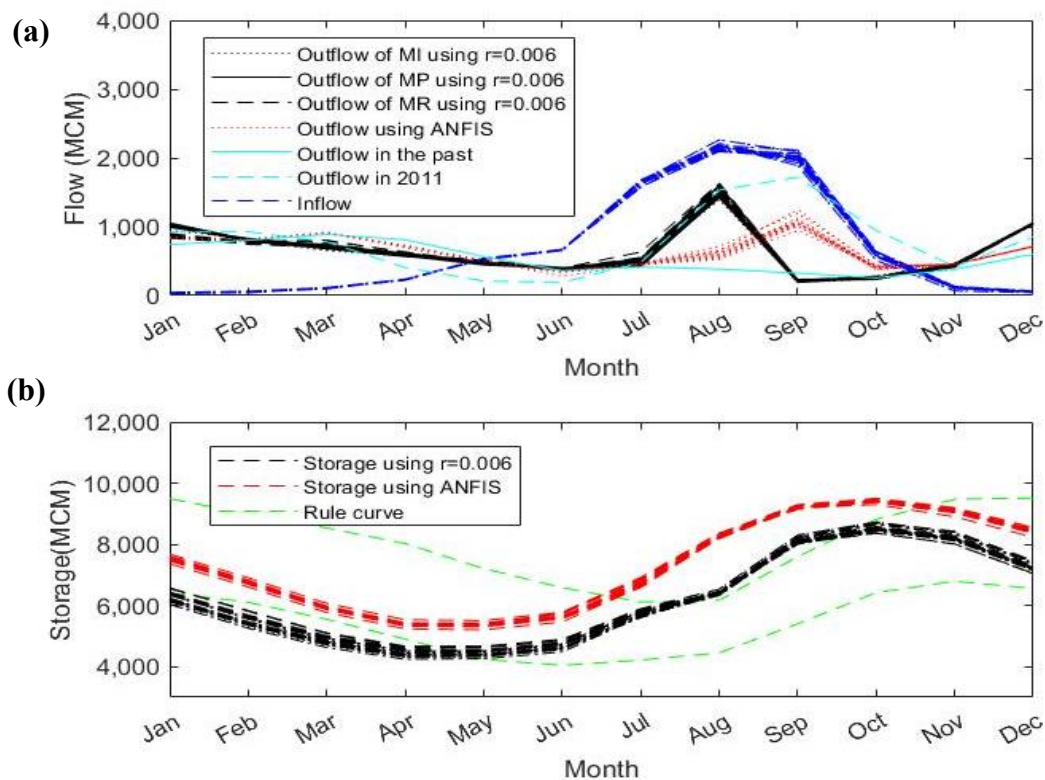


Figure 6.24 Future trends of (a) monthly inflow, reservoir water release, and (b) storage for the reservoir operation of Sirikit Dam

During the dry season (November to April), the future reservoir water release is about 800-1,000 MCM per month (Figure 6.24(a)). Noticeable, the water release *via* the ratio (r) of 0.006 is about 100-200 MCM higher than the ANFIS model. At the beginning of the rainy season, the discharge decreases less than 500 MCM per month. The inflow dramatically increases starting in June, and the inflow peak is approximately 2,200 MCM in August. During the high inflow period, the reservoir releases using the ratio ($r = 0.006$) are in the range of 500-1,800 MCM per month. In contrast, through the ANFIS model the dam discharges only 500-1,200 MCM per month after the highest inflow. Since the dam discharges more water through the additional reservoir operation, the storage volume is lower than the ANFIS model (Figure 6.24(b)).

More specially, the histograms of inflow and reservoir discharge using the MRm107 ensemble member of the years 2091-2110 are shown in Figure 6.25. During the rainy season, the inflow is generally less than 100 MCM per day, and the maximum inflow is 456 MCM per day (Figure 6.25(a)). Due to the high amount of inflow, the Sirikit Dam should have more space to capture the maximum inflow in the future. In the model, after the highest inflow, the reservoir has to discharge 70-80 MCM per day over a week to maintain water level. On the other hand, 50% of the total days of the dry season are estimated to be dry days (Figure 6.25(b)). About 15-45 MCM/day is released to meet water demands on the downstream (Figure 6.25(d)).

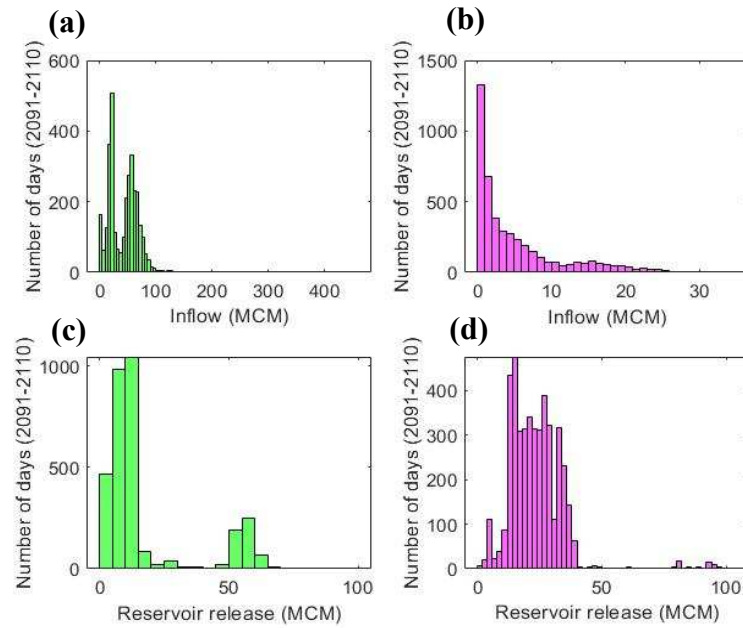


Figure 6.25 Histograms of the years 2091-2110 for Sirikit Dam using the MRm107 ensemble member indicating inflows during **(a)** the rainy season **(b)** the dry season, and reservoir water releases during **(c)** the rainy season and **(d)** the dry season

In short, the maximum monthly inflow of Bhumibol Dam is greater than of Sirikit Dam due to the reservoir catchment area. However, the daily inflow of Sirikit Dam could lead to 400 MCM/day, because the annual rainfall on the upstream is above 3,000 mm/year. Since the dams release more water volumes before the highest inflow through the additional reservoir operation, both dams will have sufficient volume to capture the massive inflow in the future. Moreover, both dams may have available water of about 6,000-8,000 MCM in total to meet water demands during the dry season. These significant findings should be taken into account for the future reservoir operations in terms of effective flood protection and water demands meeting.

6.5 Summary

This chapter aims to construct ANFIS models to simulate daily reservoir releases for Bhumibol and Sirikit Dams. In order to optimize the performance of the model, input parameters, forms and numbers of MFs, and additional set-ups have been taken into account. The suitable form of membership functions (MFs) has been selected as the first priority. From the eight forms of MFs, it was found that the trapezoidal-shaped membership function leads to the best result to construct a reservoir operation model. Then, basic input parameters (inflow, storage, rainfall, and water demand) and additional considerations of seasonality and the month have been applied. For the basic parameters, the adjustment of numbers of MFs for inflow and storage inputs has the significant improvement of model performance. In contrast, more complexity of numbers of MFs for rainfall and water demand inputs does not tend to improve the performance. The set-up of seasonality could increase the performance, especially for the ANFIS model of Sirikit Dam due to the dam operation is based on the seasonal pattern. With regards to additional monthly input, the model performance of Bhumibol Dam is greatly increased since the water discharge depends on monthly antecedent effective storage ratios. Consequently, an additional monthly parameter expressed the best performances leading to NSE values of 0.43 and 0.47 for Bhumibol Dams and Sirikit Dam, respectively.

In order to achieve an effective reservoir operation, additional reservoir operations have been suggested for the timing and the daily release storage ratios (r). The simulated water release by adding the daily release storage ratio (r) of 0.006 is recommended to use at the mid-rainy season (July-August), and the ratio (r) of 0.001 should be applied at the end of the rainy season (September-October). These ratios were examined by their

impacts on river flow, and the results show that the flood peaks could be decreased. In consideration of drought mitigation, the operation was designed to increase the daily water release of 14 MCM for Bhumibol Dam and 7 MCM for Sirikit Dam when the Lower CPRB has no rainfall for over seven days.

The optimized performances of ANFIS models and the additional reservoir operation for both dams have been applied to future climate data of two periods (2051-2070 and 2091-2110). The dams discharge about 700-1,200 MCM per month during the dry season. About 500-2,000 MCM per month and less than 400 MCM per month are released at the mid and the end of rainy seasons, respectively. In total, through rainy season about 6,000-8,000 MCM could be stored to support water on downstream. In the future, the available water from both dams should be taken into account to meet water demands for effective dam operations.

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Chapter 7

Impacts of the Combination of Climate Change, Reservoir Operations, and Pond Management on Flow Regime

7.1 Introduction

Climate change and other consequences of human activity affect the flow regime in general. The most significant aspect of climate change is that the effects are often uncontrollable, especially floods and droughts. However, disasters can be prevented and/or mitigated by human interventions such as water resources management. In the case of the latter, large-scale reservoirs are key to control downstream flows on the Chao Phraya River Basin (CPRB). The stability of water supply and mitigation of floods and droughts apparently depend on the reservoir operations. It has also been reported that the maximum runoff decreases during high flow and that the minimum runoff increased downstream of Ping, Nan, and Chao Phraya Rivers after the Bhumibol and Sirikit Dams were constructed (Tebakari *et al.*, 2012). In changing runoffs *via* the construction of both dams, the river discharge at downstream also affected, and the flow peaks could be increased or decreased depending on dam operations. Mis-operation of large-scale dams, however, can turn this opportunity into risk, as the experience of 2011 floods showed. Late reservoir releases at the flood peaks in 2011 caused devastating damages in terms of losses and deaths (World Bank, 2012). Effective reservoir operations should examine how

the downstream discharges will be influenced in the future by taking into account the extreme rainfalls associated with climate change.

Additionally, the huge number of small-scale water resources such ponds also influence runoffs and river discharge. In CPRB, over 78,000 units of existing ponds have been constructed/operated under the Thai government projects. Due to its large number, mismanagement of ponds might have negative impacts on flow regime such as increased flood peaks through pond overflows. In contrast, flood and drought might be avoided by effective pond management.

Since the large and small scales of reservoirs are significant strategies of water resources management, this chapter aims to examine the impacts of climate change, reservoir operations and pond management on the CPRB's flow regime. In particular, the first objective is to predict how river discharges will be reacted through future reservoir releases and extreme rainfall events (heavy and consecutive no rainfalls). Also, Chapter 5 have suggested the appropriate pond capacities, pond management, and the number of future ponds in considerations of local conditions and climate change. In order to use proper pond management in the future, the second purpose is to evaluate the impacts of pond management on flows at the Upper and Lower CPRB, especially for flood and drought mitigation.

7.2 Methodology

In order to simulate the impacts of water resource strategies on flow regime, mainly four models from the previous chapters are combined in this chapter, as shown in Figure 7.1.

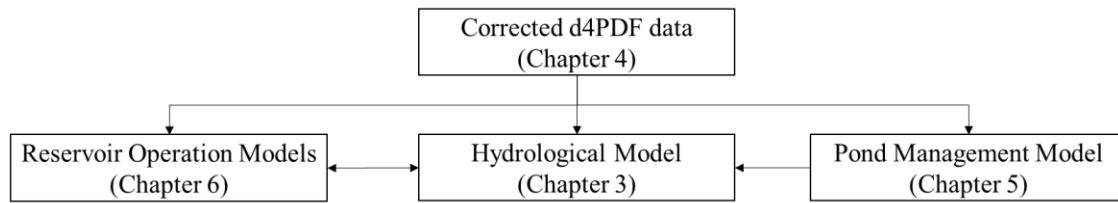


Figure 7.1 Framework of the methodology

For future climate data preparation, Database for Policy Decision-Making for Future Climate Change (d4PDF) have proceeded for three ensembles (MI, MP and MR ensembles) in which each ensemble contributes to 15 members of two periods: 2051-2070 and 2091-2110. The post-processing d4PDF outputs, including daily rainfall and temperature from Chapter 4, has been used in three models: the hydrological model in Chapter 3, the pond management model in Chapter 5, and the reservoir operation model in Chapter 6.

7.2.1 Hydrological Model

In the Hydrological Model using Hydrological Simulation Program-Fortran (HSPF), daily rainfall, maximum temperature and minimum temperature of 45 ensemble members of corrected d4PDF outputs were prepared in time series data using a specific file (.wdm file) *via* SARA Timeseries Utility. The tool has computed potential evapotranspiration (PET) data *via* Hamon PET method in which the daily maximum and minimum temperature time series were inputs, and the latitude of each d4PDF grid station was identified. In the model, the climate data at 57 gridded stations were set over the CPRB area as in Figure 7.2. In particular, the relationship between each sub-basin and grid stations was determined by Thiessen Polygon method (Fiedler, 2003). Since large reservoir operations impact on downstream flow regime, the model has been developed

and set with inputs from the simulated reservoir discharges of Bhumibol and Sirikit Dams which are computed *via* the reservoir operation model.

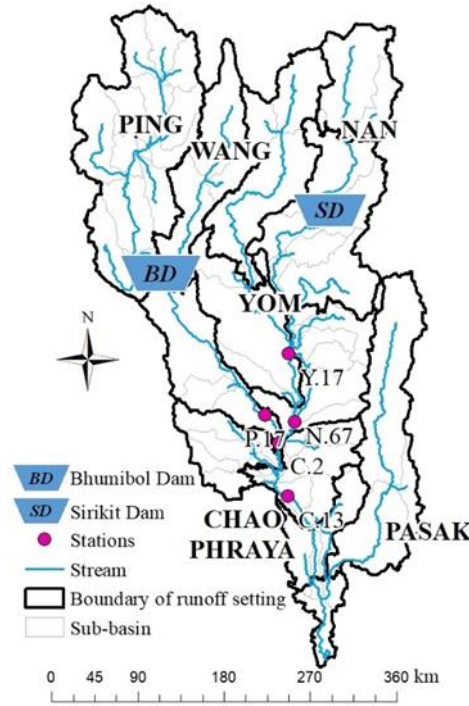


Figure 7.2 Locations of two reservoirs and river discharge stations and boundaries of sub-basins and runoff settings

7.2.2 Reservoir Operation Model

As the results of optimal model performances of Bhumibol and Sirikit Dams in Chapter 6, four basic parameters (inflow, storage, rainfall, and water demand) are essential. Daily inflow time series data have been simulated at upper parts of Bhumibol Dam and Sirikit Dam in the hydrological model. The corrected rainfall data from the post-processing d4PDF outputs were prepared in Chapter 6, and daily water demand data were calculated by the water requirements model in Chapter 5. Daily storage volume was simultaneously simulated at interval-to-interval by the basic water balance equation in the reservoir operation models. Those essential parameters with an additional monthly

parameter have optimized the performance in simulations of daily discharges of both reservoirs. Moreover, the additional reservoir operation using the daily release storage ratios (r) and additional water release were applied for protections of floods and droughts. The daily release storage ratios of 0.006 and 0.001 have been suggested to control water releases during the mid and end of rainy seasons, respectively. For drought mitigation, the operation was designed to increase daily water release of 14 MCM for Bhumibol Dam and 7 MCM for Sirikit Dam when the Lower CPRB has no rainfall over seven days. Through the optimized model performance and additional reservoir operation, future reservoir discharges of Bhumibol and Sirikit Dams for 45 datasets of the years 2051-2070 and 2091-2110 were predicted using climatological data. In the hydrological model, each reservoir discharge dataset was also prepared in the specific file as a similar procedure in Section 7.2.1. Finally, the hydrological model could simulate the future river discharges. Regarding main streams, the annual maximum daily flow, the number of days with no flow per year, and the number of days with overflow per year were obtained at the stations P.17, N.67, Y.17, C.2, and C.13 which are in the down-streams of Ping, Nan, and Yom River, the origin of CPR, and mid-stream of CPR, respectively (Figure 7.2).

7.2.3 Pond Management and Hydrological Model

In the CPRB, over 68,000 on-farm ponds and 10,000 public ponds are existing for agriculture and multi-purposes. Due to the large numbers, appropriate pond operations in terms of flood and drought protection and water demand meets have been recommended in Chapter 5. Additionally, numbers of future ponds with suitable pond capacities related to the insufficient irrigation water and economic analysis have resulted in 2,024 sub-districts. The change of pond management and increase of future pond numbers might

affect river discharge hydrograph. In order to examine the impacts of pond management on CPRB's flow regime, the daily pond inflow and release were calculated through 68,177 private ponds, 3,295 public ponds, and 777,391 units of the future ponds, indicated as the results of Chapter 5.

Regards to the changes of daily pond inflows and outflows, the volume changes of all ponds, including existing ponds and future ponds in each sub-basin were combined in a calculation of sub-basin runoff change. Relate to the hydrological model using HSPF, the runoff change in daily time series were prepared and set through a special command. Since the complicated setup of each sub-basin in the HSPF model causes time-consuming of the model running, the changes in sub-basin runoffs related to daily pond inflow/release were performed by 13 groups of sub-basins in Figure 7.2.

In order to understand how pond management could change the flow regime, historical climate data of the years 2001-2010 through observation and post-processing d4PDF outputs were inputs in the hydrological model with setting runoff changes from ponds. With regards to the extreme rainfall events including very high and low rainfall amounts, three ensembles (MI, MP and MR) of future climate datasets were simulated to predict impacts. After hydrological simulations, the changes of river discharges are also represented using the annual maximum daily flow, the number of days with no flow per year, and the number of days with overflow per year at the stations P.17, N.67, Y.17, C.2, and C.13.

7.3 Results and Discussion

7.3.1 Impacts of Climate Change and Reservoir Operations

In order to predict future river discharges, the 45 datasets of future climate with the reservoir operations of Bhumibol Dam and Sirikit Dam were input in the hydrological model. In general, both large scale reservoirs affect low and high flows at the downstream of Ping and Nan River Basin, as shown in Figures 7.3 and 7.4. During the low flow, the Bhumibol Dam releases about 300-700 m³/s of water. About 500-1,200 m³/s of water are always released to keep space of storage at the mid of the high flow. In contrast, the dam discharges a small amount of water which is less than 300 m³/s during the end of the high flow. Particularly, when the reservoir storage is closed to the capacity, the high amount of water was commanded to release even the river water level is high, as shown in Figure 7.3(b).

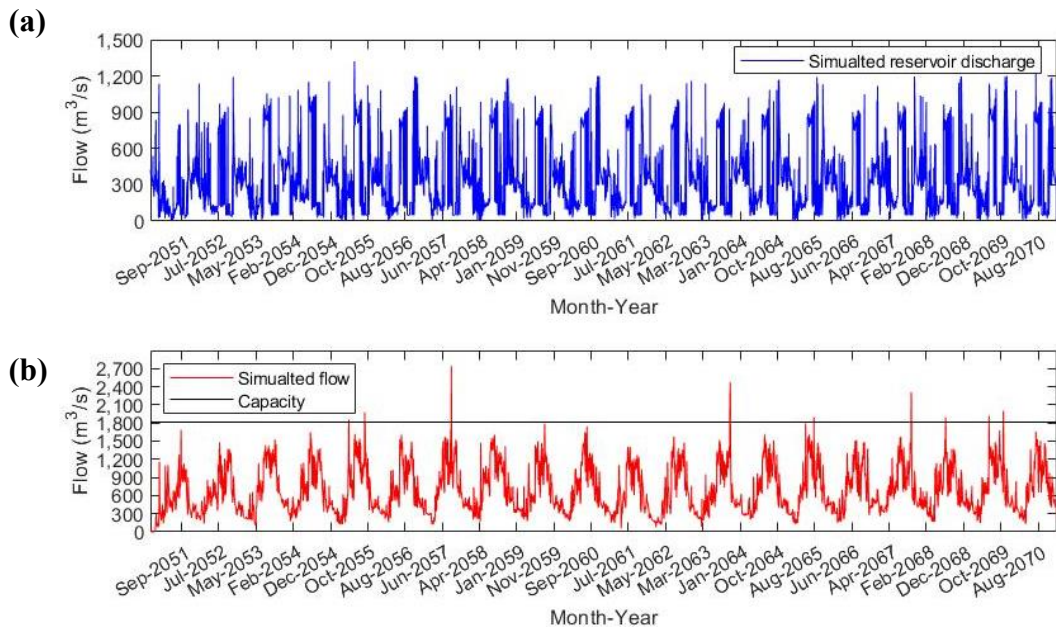


Figure 7.3 (a) Reservoir discharge of Bhumibol Dam and **(b)** simulated river discharge at the station P.17, Ping River

Given the trend of Sirikit Dam's operation, the daily reservoir releases are normally less than 400 m³/s (Figure 7.4(a)). High water discharge is projected at the end of high flow (Figure 7.4(b)). However, the dam operation is not only one factor to attenuate flow peaks. As pointed to the maximum daily flows in the years 2055 and 2066, Sirikit Dam releases water in the range of 600-700 m³/s while the river discharges rise to 3,000 m³/s at the station N.67.

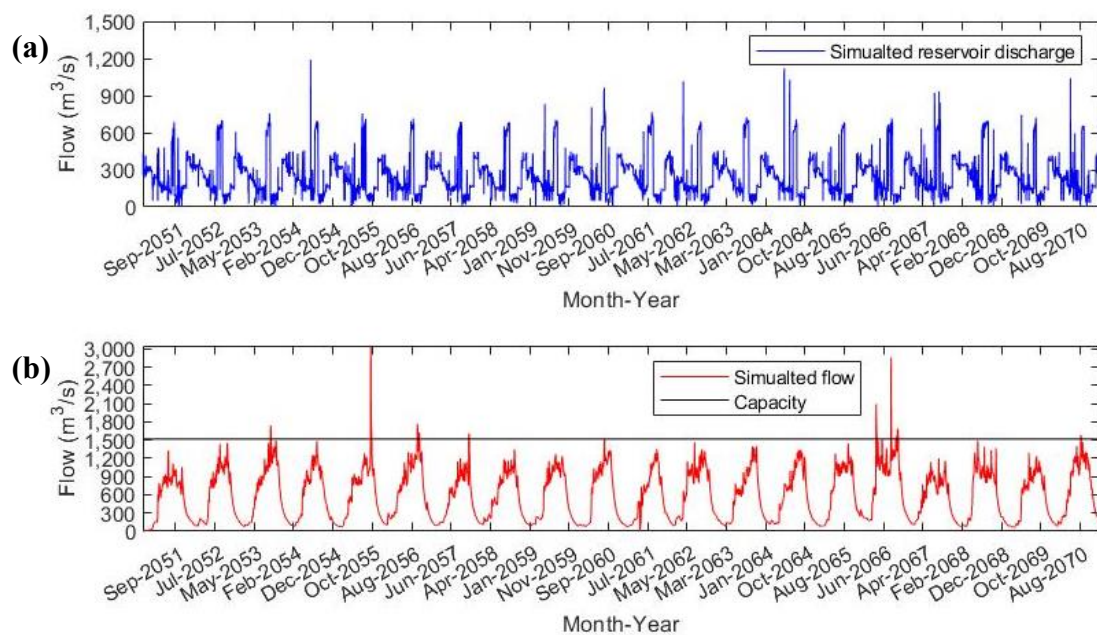


Figure 7.4 (a) Reservoir discharge of Sirikit Dam and **(b)** simulated river flow at the station N.67, Nan River

As the results, rainfall intensity in each area also affects to the highest flow peak year after year. Climate change data of three ensembles (MI, MP, and MR) of two periods (2051-2070 and 2091-2110) were performed to predict river discharges. Non-exceedance probabilities of annual maximum daily flow, the number of days with overflow per year, and the number of days with no flow per year are presented at the stations Y.17, N.67, P.17, C.2, and C.13 in Figures 7.5 to 7.9.

With regards to three ensembles of climate change data, the values of annual maximum daily flows vary at the very low values ($p < 0.01$) and very high values ($p > 0.95$) of non-exceedance probability, as shown in Figure 7.5(a). In the difference, the annual maximum daily flow of MP ensemble of the years 2051-2070 expresses the annual highest flow in a range of 500-1,300 m^3/s ($p < 0.01$). At the extreme peak flow ($p > 0.995$), the annual maximum daily discharge stands about 3,500-5,000 m^3/s . Since the current river capacity of the station Y.17 is 480 m^3/s , overflows can occur from 40 to 220 days in a year, as shown in Figure 7.5(b). In order to protect future overflows, the 0.95 of non-exceedance probability should be used to capture the high range of annual maximum daily flow. Based on this value, the station Y.17 should increase the river capacity at least 2,500 m^3/s .

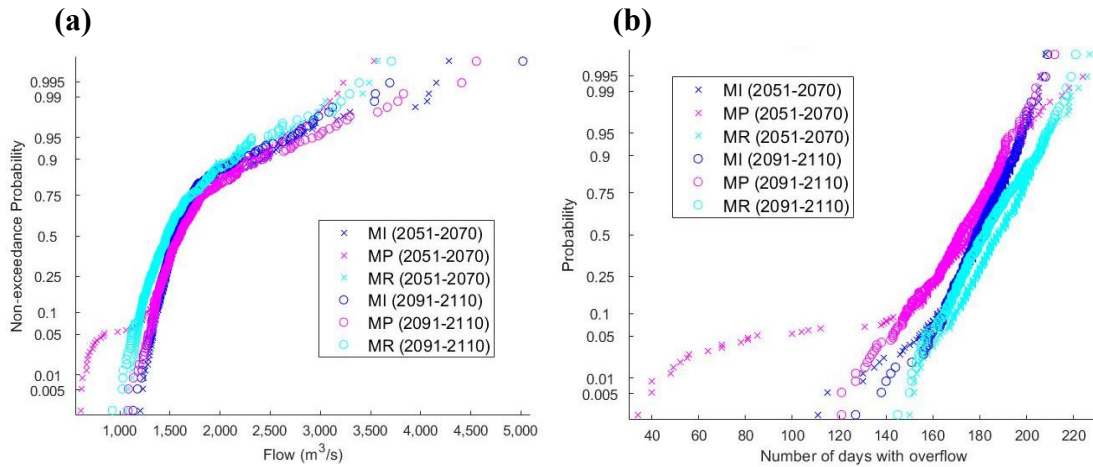


Figure 7.5 Probabilities of (a) annual maximum daily flow and (b) the number of days with overflow per year using three ensembles (MI, MP and MR) of the periods 2051-2070 and 2091-2110 at the station Y.17, Yom River

Because the flows from the station Y.17 merge into the station N.67, the annual maximum daily flows at both stations are generally in a similar trend as shown in Figure 7.6(a). Moreover, the extreme peak flows ($p > 0.995$) of MI and MP ensembles of the years

2091-2110 are about 4,000-5,300 m³/s. In Figure 7.6(b), the number of days with overflow is predicted to be less than 60 days. Due to 1,520 m³/s of the river capacity of the station N.67, its capacity could secure the annual highest peak flow when the probability is lower than 0.25.

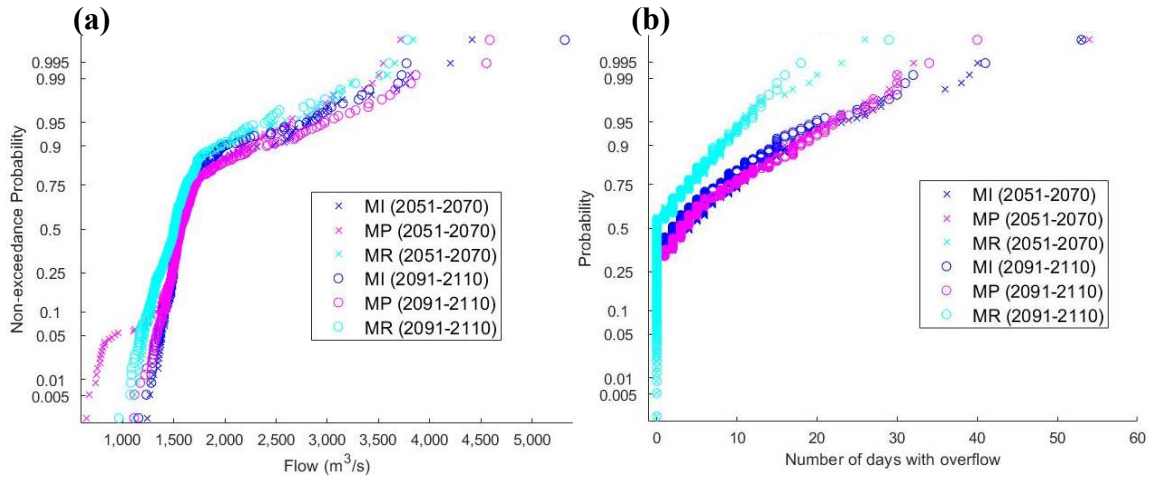


Figure 7.6 Probabilities of (a) annual maximum daily flow and (b) the number of days with overflow per year using three ensembles (MI, MP and MR) of the periods 2051-2070 and 2091-2110 at the station N.67, Nan River

Prediction of annual maximum daily flow at the station P.17 indicated a parallel trend *via* three ensembles, as shown in Figure 7.7(a). The number of overflowing days in a year is small (Figure 7.7(b)) because the river capacity of 1,815 m³/s can capture 75% of overflow frequency. This capacity, however, might not be enough to protect future extreme overflows, especially over 2,000 m³/s at the non-exceedance probability higher than 0.9. The river also has the possibility to dry up when the longest drying days could be 80 days, as shown in Figure 7.7(c). The water scarcity is mainly caused by the annual rainfall. More specifically, in Chapter 4 we mentioned that the annual rainfall is approximately 500-1,000 mm/year at the downstream of Ping River Basin, where the

station P.17 locates. For the future plan, river capacity increase and special river management for drought mitigation are a priority concern for the station P.17.

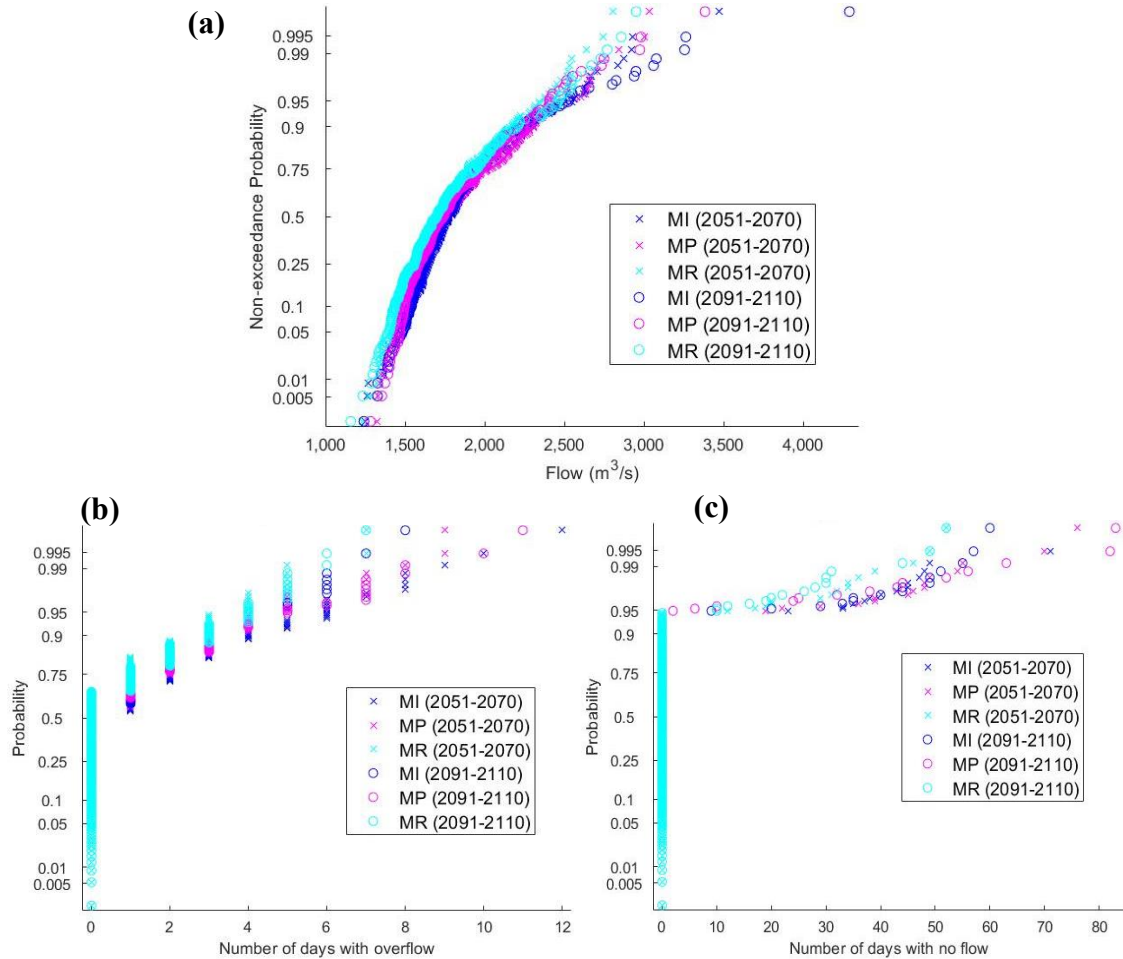


Figure 7.7 Probabilities of (a) annual maximum daily flow, (b) the number of days with overflow per year, and (c) the number of days with overflow per year using three ensembles (MI, MP and MR) of the periods 2051-2070 and 2091-2110 at the station P.17, Ping River

Since the flows from the stations N.67 and P.17 combine at the station C.2, the origin of Chao Phraya River, the annual maximum daily flows are much higher than previous stations as shown in Figure 7.8(a). The normal peak flow tends to be larger than 2,500 m^3/s . Particularly, the extreme peak flow ($p > 0.995$) could be in the range of 5,500-6,800 m^3/s . However, the current river capacity is 3,590 m^3/s . When the probability is higher

than 0.5, the annual maximum peak flow is out of the capacity. In the estimation of the number of days with overflow per year, the overflow can occur within two months (Figure 7.8(b)).

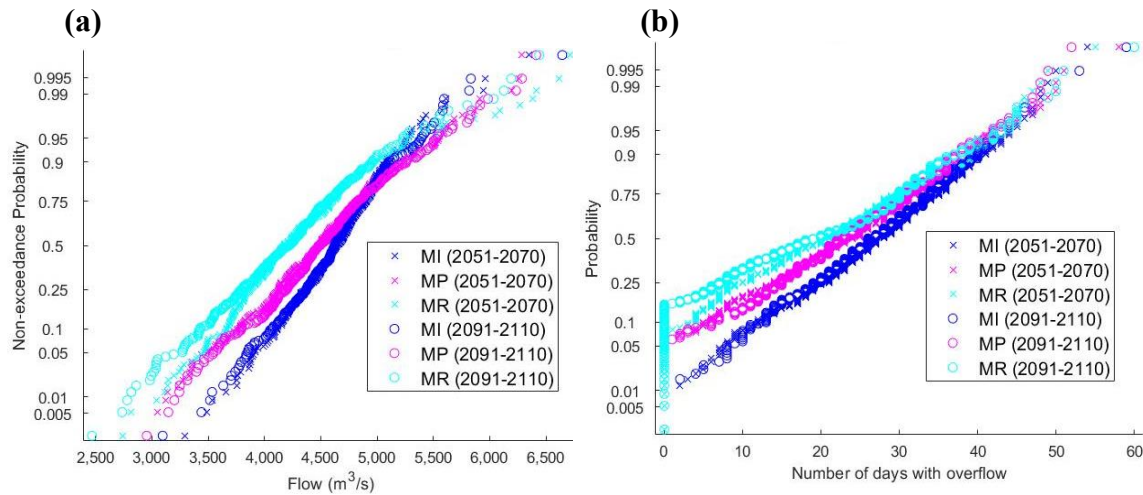


Figure 7.8 Probabilities of (a) annual maximum daily flow and (b) the number of days with overflow per year using three ensembles (MI, MP and MR) of the periods 2051-2070 and 2091-2110 at the station C.2, Chao Phraya River origin

At the mid-stream of Chao Phraya River (the station C.13), the range of extreme peak flows, 4,000-5,800 m^3/s in Figure 7.9(a), is smaller than the river origin because some amount of waters splits from the main river through the Thachin River and two large canals before the station C.13. Within the capacity of 2,840 m^3/s , the yearly overflow duration is about one month for normal situations and approximately 63 days for the most prolonged duration (Figure 7.9(b)). No flows at the mid-stream also have been evaluated within three months when the probability is over 0.9. It causes low rainfall intensity, high water demand, and water withdrawal from numerous canals and irrigations.

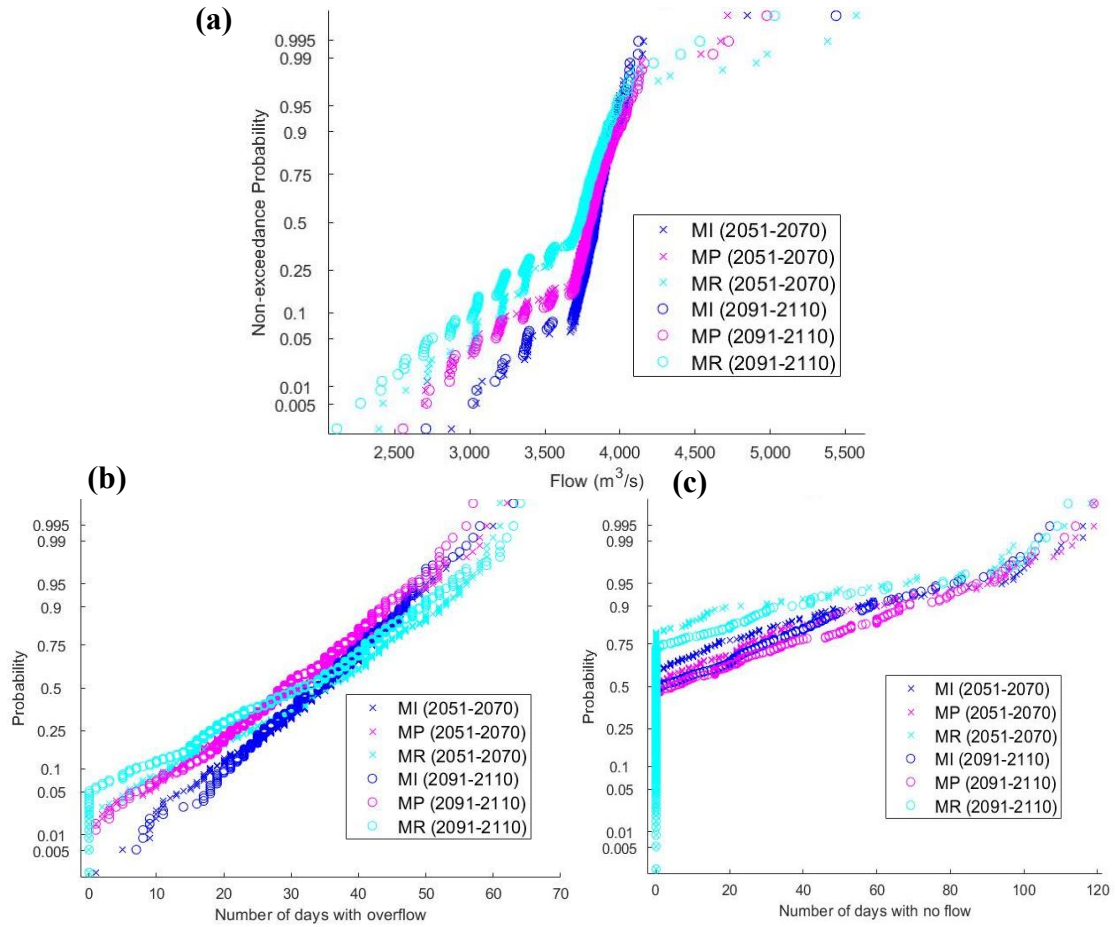


Figure 7.9 Probabilities of **(a)** annual maximum daily flow, **(b)** the number of days with overflow per year, and **(c)** the number of days with overflow per year using three ensembles (MI, MP and MR) of the periods 2051-2070 and 2091-2110 at the station C.13, mid-stream of Chao Phraya River

In short, the flood frequency analysis using the annual maximum daily flow and the non-exceedance probability of three ensembles were projected that the flood distributions of the period 2091-2110 are markedly greater than the period 2051-2070, particularly for the extreme discharge of the five stations. Because the initial conditions (greenhouse gases, aerosols and ozone) of d4PDF data based on the year 2090, the rainfall distributions are accordingly increased after the year 2090 (Mizuta *et al.*, 2017). These affect the increases in the highest peak flows of the years 2091-2110. Regarding the duration of

overflow, the number of days with overflow in each basin is related to the current river capacity. Increase of the river capacities should be considered to minimize the overflow frequency in the future. Focusing on the river capacity may not be sufficient for the stations P.17 and C.13 since the water scarcity of both stations has assessed in a term of the number of days with no flow. Hence, special water management is required to operate low flows in the downstream of the Ping River and mid-stream of Chao Phraya River.

7.3.2 Impacts of Pond Management

Given the purpose to understand how flow regime is affected by pond management, changes of daily runoffs *via* pond management were simulated in the hydrological model using the historical observed and corrected climate data of the years 2001-2010. The results of daily river discharge at the stations Y.17, N.67, P.17, C.2, and C.13 are illustrated for the Upper and Lower CPRB in Figures 7.10 and 7.11, respectively. At the Upper CPRB, the river discharge peaks at the beginning of rainy seasons (May-July) are slightly increased through setting pond management. In general, the river discharges at the station Y.17 are over the river capacity day after day during the rainy season (May-October) due to the inadequate river capacity of 480 m³/s as shown in Figure 7.10(a). By the control of pond releases, the flows could be reduced at the end of the rainy season (August-October), then the flows rise up in small amounts during the low flow (Jan-April). At the station N.67 (Figure 7.10(b)) the flows are generally decreased at starting low flow period and the end of the rainy season since the runoff decreases from pond storing more of rainfall water. In Figures 7.10(b) and 7.10(c), the flows at stations N.67 and P.17, respectively, located at the downstream of Nan and Ping Rivers are obviously reduced about 900-1,200 m³/s at the flood peaks of the years 2002 and 2006. Since over 50% of

the total number of ponds are in both basins, the ponds upstream to them were commanded in the model to store more waters as artificial water storages for flood protection.

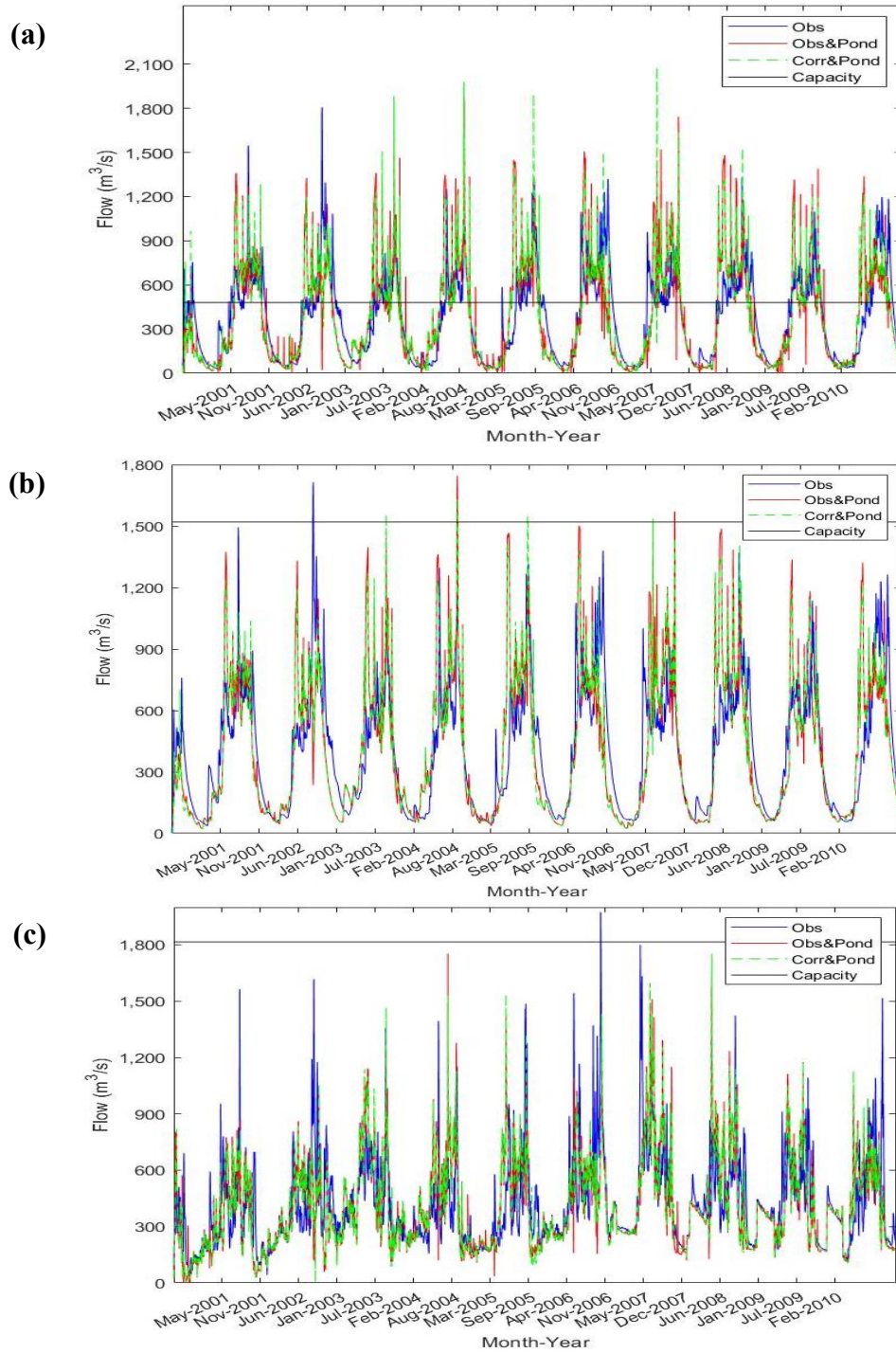


Figure 7.10 Impacts of pond management on daily flows in the Upper CPRB at the stations **(a)** Y.17, **(b)** N.67, and **(c)** P.17

In consideration of changes at the Lower CPRB (Figure 7.11), the significant finding is that the pond management could protect overflows in reducing over 2,000 m³/s of the flood peaks of the years 2002 and 2006. For other years, the flows at the beginning of rainy seasons, July to August, the rise more than 800 m³/s and 1,000 m³/s at the stations C.2 and C.13, respectively. As the previous results, the pond management does not affect significantly at the Upper CPRB in term of flood protection due to the insufficient river capacities. The overflow protection of both flood years showed an advantage of pond management at the Lower CPRB.

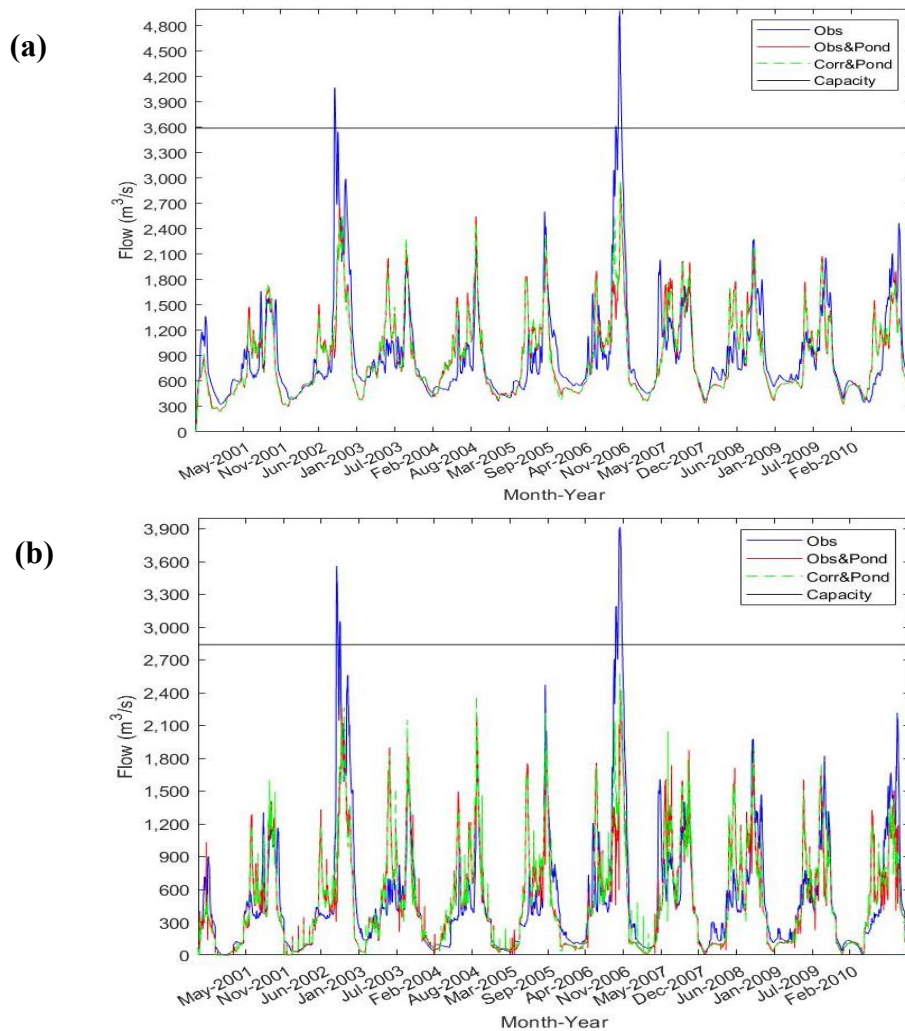


Figure 7.11 Impacts of pond management on daily flows in the Lower CPRB at the stations **(a)** C.2 and **(b)** C.13

7.3.3 Impacts of Pond Management in Future

In addition, future climate change and reservoir operations were combined with pond management to obtain well-grounded impacts on the flow regime. The non-exceedance probabilities of annual maximum daily discharge and the number of days with overflow per year are compared between the original and combined simulations. The original simulation was resulted from climate change and reservoir operation setups as described in Section 7.3.1, and the combined simulation was added a pond management setup. Since there is a connection between the stations Y.17 and N.67, a similar trend of annual maximum daily flow is shown in Figures 7.12(a) and 7.13(a). When the non-exceedance probability is higher than 0.90, the annual maximum daily flows *via* pond management are decreased. However, the flows ($p < 0.90$) tend arising approximately 500 m³/s from the original setup at the stations Y.17 and N.67. This causes changes of discharge peak occurrence in timing and quantity as an example of daily flow at the station N.67 shown in Figure 7.14.

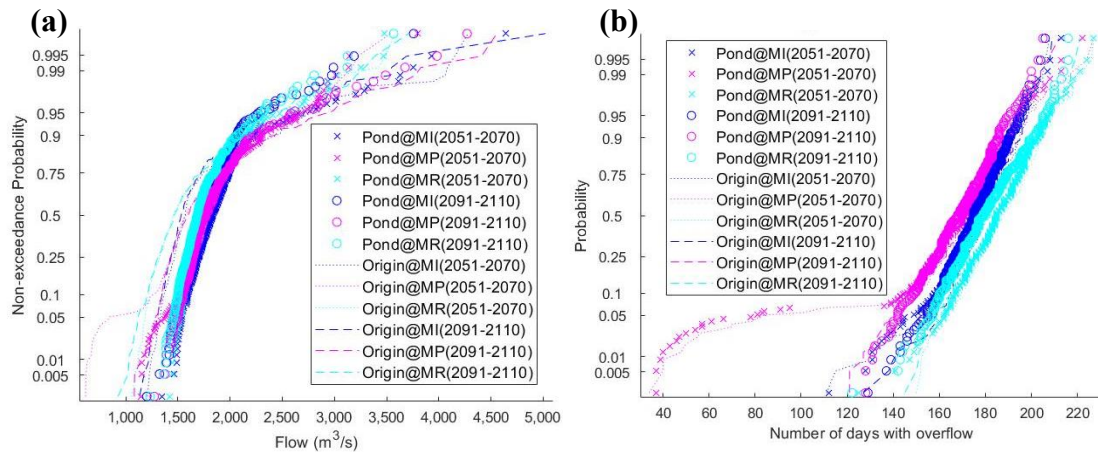


Figure 7.12 Probabilities of (a) annual maximum daily flow and (b) the number of days with overflow per year through the pond management setup and three ensembles (MI, MP and MR) of the periods 2051-2070 and 2091-2110 at the station Y.17, Yom River

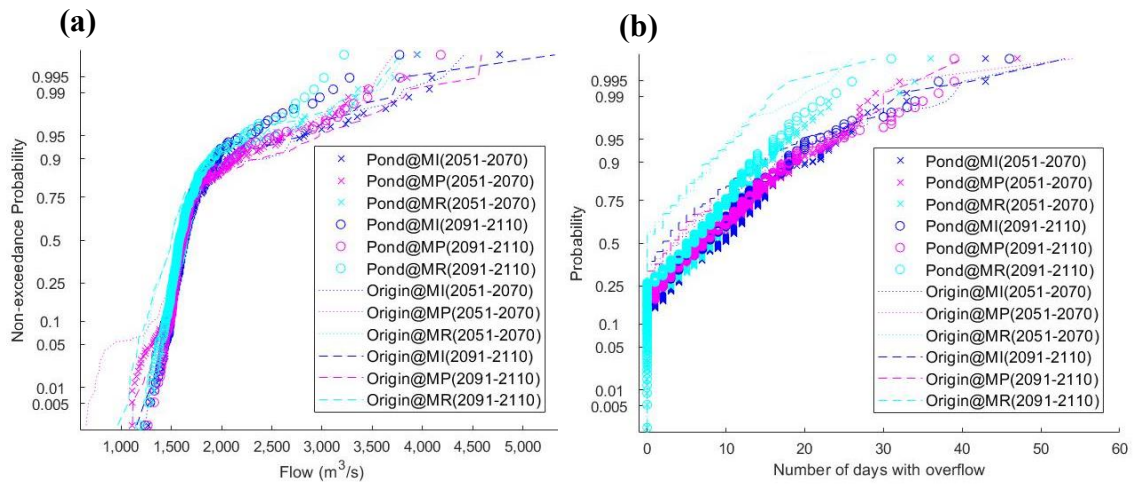


Figure 7.13 Probabilities of **(a)** annual maximum daily flow and **(b)** the number of days with overflow per year through the pond management setup and three ensembles (MI, MP and MR) of the periods 2051-2070 and 2091-2110 at the station N.67, Nan River

Based on the characteristic of the flow regime, the highest flow peak always occurs at the end of rainy seasons. By the pond management setup in Figure 7.14, the high flow peaks in some years are changed from September to June. The timing of maximum flow occurrence is shifted because numerous ponds were commanded to release more water at the beginning of rainy seasons. Within rising rainfall intensity during the period 2091-2110 at the upstream of Nan River as a result in Chapter 4, pond water releases have an effect by increasing the overflow frequency (Figure 7.14(b)). Moreover, the annual maximum daily flow is projected to increase by about 500-1,000 m^3/s .

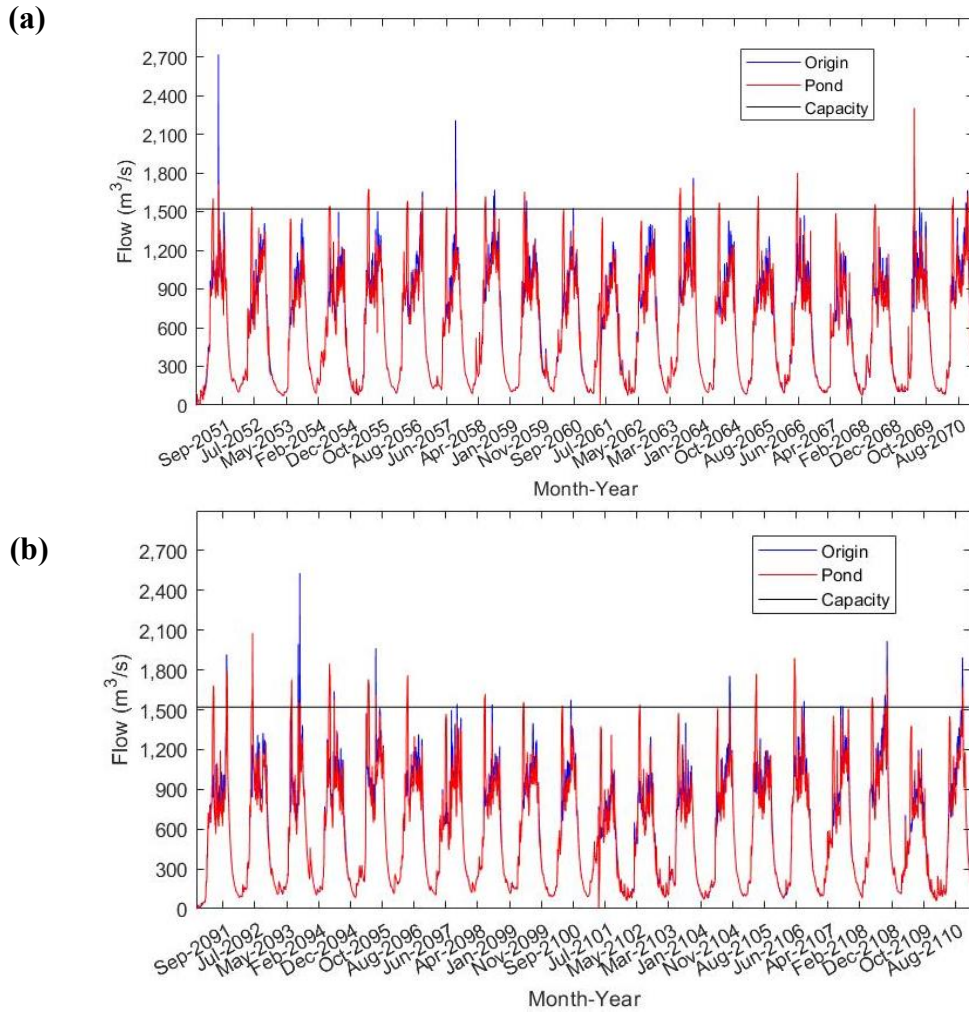


Figure 7.14 Impacts of pond management on daily flows at the station N.67 using ensemble member MR m108 of the periods **(a)** 2051-2070 and **(b)** 2091-2110

At the station P.17, the distributions of highest peak flows showed insignificant change when including pond management setup (Figure 7.15). The annual maximum daily flow slightly decreases at the high value of non-exceedance probability ($p > 0.99$). Also, the number of days with no flow reduces considerably about 2-10 days from the original setting (Figure 7.15(b)).

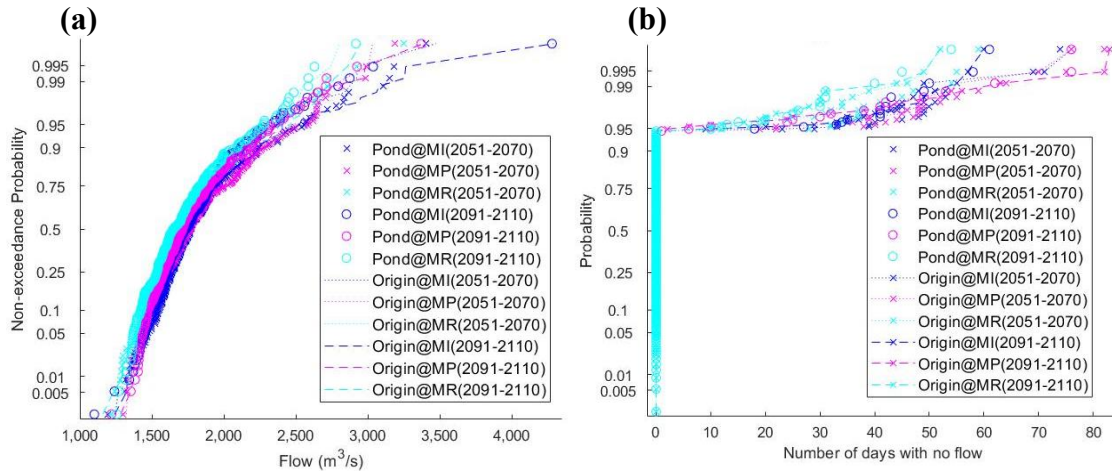


Figure 7.15 Probabilities of (a) annual maximum daily flow and (b) number of days with no flow per year through the pond management setup and three ensembles (MI, MP and MR) of the periods 2051-2070 and 2091-2110 at the station P.17, Ping River

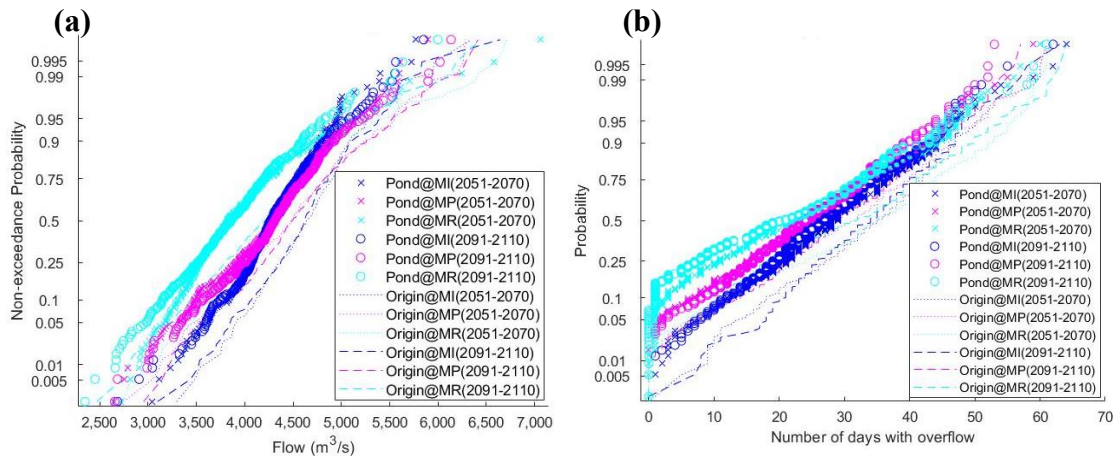


Figure 7.16 Probabilities of (a) annual maximum daily flow and (b) the number of days with overflow per year through the pond management setup and three ensembles (MI, MP and MR) of the periods 2051-2070 and 2091-2110 at the station C.2, Chao Phraya River origin

Due to the slight decrease in upstream flows, the distributions of annual maximum daily flows at the stations C.2 and C.13 accordingly became smaller by 300-500 m^3/s from the original setup, as shown in Figures 7.16(a) and 7.17(a). The overflow frequency decreases as well as the annual maximum daily flow (Figures 7.16(b) and 7.17(b)). A significant impact of pond management is that it could reduce the extreme flows about

500-2,000 m³/s when the non-exceedance probability is higher than 0.95. Moreover, the distributions of the number of days with no flow at the station C.13 tend to reduce water shortage duration, as shown in Figure 7.17(c). Approximately 5-20 days with no flow could be reduced *via* pond management setup.

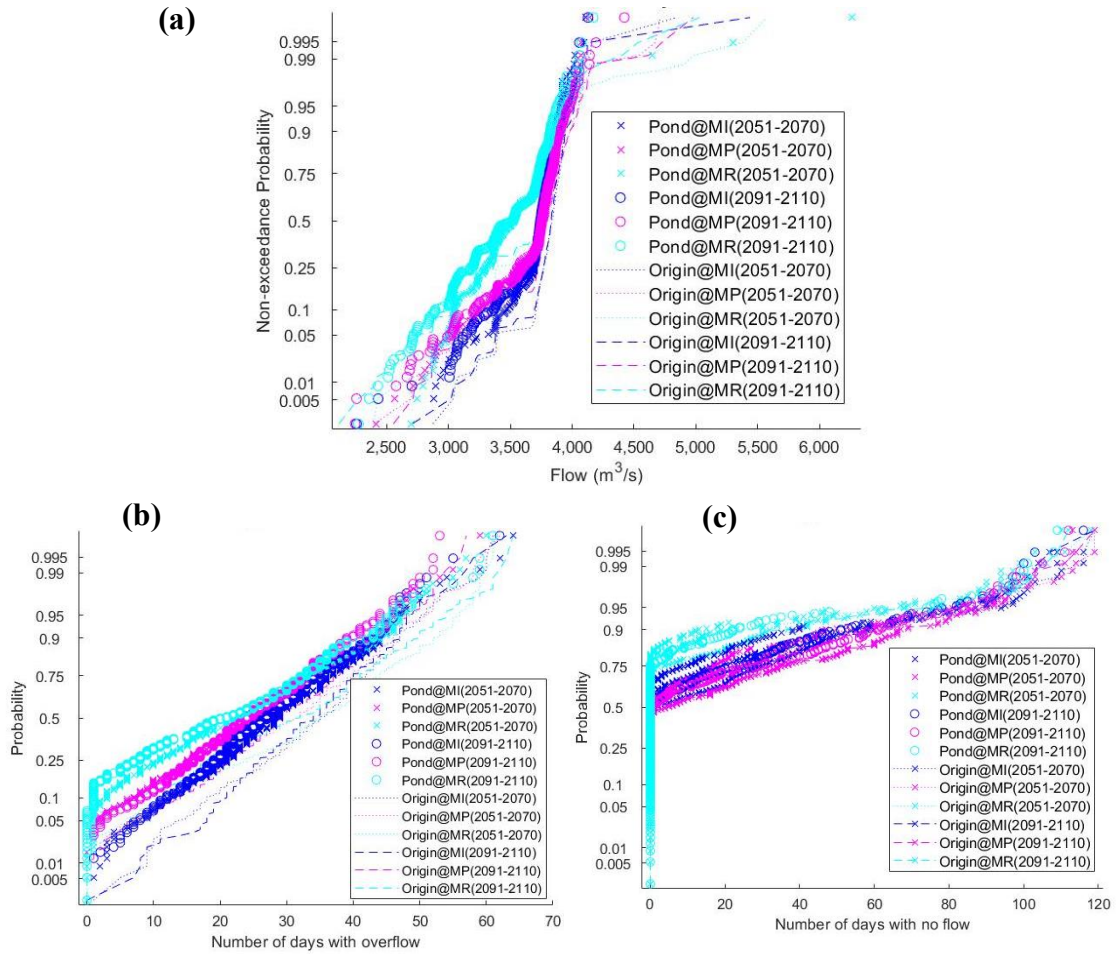


Figure 7.17 Probabilities of (a) annual maximum daily flow, (b) the number of days with overflow per year, and (c) the number of days with overflow per year through the pond management setup and three ensembles (MI, MP and MR) of the periods 2051-2070 and 2091-2110 at the station C.13, midstream of Chao Phraya River

7.4 Summary

The impacts of climate change and reservoir operations were assessed on the CPRB's flow regime. Flood frequency analysis through the annual maximum daily flow and non-exceedance probability were conducted at the stations Y.17, N.67, P.17, C.2, and C.13 located at Yom, Nan, Ping, and Chao Phraya Rivers, respectively. From the flood frequency distributions, it was found that the flood frequency of the period 2091-2110 is greater than the period 2051-2070, especially at the extreme peak flows, when the probability is higher than 0.95. Increases in river capacities of the stations Y.17, N.67, C.2, and C.13 are a significant concern for the future water management plan. Due to the decrease of future annual rainfall at the downstream of Ping River, the days with no flow might be up to 80 days at the station P.17. Also, extremely water shortage for three months was projected at the Lower CPRB. Consequently, proper water management should be taken into account for mitigation of future drought events in the Ping River and mid-stream of Chao Phraya River.

In order to understand the impacts of pond management on flow regime, historical observation and d4PDF has been combined with pond management in the hydrological model. Also, the change in daily river discharge has been examined. By pond management, the river discharges arise at the beginning of the rainy season, then flows reduce at the end of the rainy season. On the Upper CPRB, the pond management slightly affects the flow regime. However, a significant finding is that pond management could have attenuated the flood peaks of 2006 and 2011 by about 2,000 m³/s on the Lower CPRB.

One of the most beneficial future impacts of pond management is the reduction of extreme peak flows at the end of rainy seasons (August-October), when the non-exceedance probability is higher than 0.95. Also, the mitigation of water shortage during the low flow at the Ping River and mid-stream of Chao Phraya River was confirmed. On the other hand, the undesirable impacts are the timing and quantity changes of the annual maximum daily flow in Yom and Nan Rivers due to the pond water releases. The annual highest flow peaks rise about 500 m³/s in July at the stations Y.17 and N.67 when the non-exceedance probability is lower than 0.90. Because of this impact on the flow regime, the timing of pond water release at the beginning of rainy seasons (May-July) should be deeply considered according to the characteristic of flow regime in each sub-basin of Yom and Nan River Basins.

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Chapter 8

Conclusions and Recommendations

8.1 Conclusions

Thailand agricultural productions are mainly derived from the Chao Phraya River Basin (CPRB) due to the characteristics of floodplain and appropriate rainfall intensity. The strengths of the region sometimes turn into weaknesses due to the impacts of climate change. More experiences of floods and droughts are received in the basin year after year, particularly after 2005. The massive floods of 2011 have affected devastating losses in terms of deaths, agriculture, property, and the economy. Consecutive droughts from 2005 to 2015 also influenced agricultural production and economic disruption. Since climate change is uncontrollable, the Thai government has started implementing new regulations of reservoir operations, proposing detention areas, and constructing ponds in the Thai Master Plan and the Free Pond Construction Project for non-irrigated areas in order to mitigate the impacts of coming floods and droughts. However, these plans have not been considered on how changes in water resources management and the future climate will respond to the flow regime. This question contributes to research purposes, in particular, to investigate the impacts of climate change and water resources management. In order to achieve it, this research was carried out. The findings obtained in this research are as follows:

Chapter 2 consists of acknowledgements and documents from the existing literature as well as consolidated deliberations on research methodology. Since climatology,

geography, topography, and hydrology are complicated and asymmetrical; simulation models are the alternative. Development of hydrological modelling based on the relationships between natural and human-made water resources has been introduced. Hydrological Simulation Program-Fortran (HSPF) model has shown to be a desirable choice of hydrological model for the CPRB due to parameter adjustments and special setups relevant to a natural phenomenon and manmade operations. Climate change and related models have been discussed in the literature reviewed for the possibility of predicting extreme future rainfall events. Policy Decision Making for Future Climate Change (d4PDF) was an advised model to apply in this research because it includes +4-K future climate simulation, the advantages of many previous models, the improvements of uncertainties, and the prediction of extreme events. Especially, the d4PDF model has not been applied yet with local climate conditions and simulated using the hydrological model in the CPRB. Moreover, post-processing climate change data, including interpolation and bias correction methods, were considered for the development approaches. In the final section, strategies of water resource management were focused on pond management and reservoir operations. Significant information was provided, such as considerations for effective management of water resources, environmental impacts, developments of pond modelling, and applications of reservoir operations.

In Chapter 3, the hydrological model has been developed using HSPF based on the characteristics of the CPRB. Three statistical parameters, namely (Nash-Sutcliffe efficiency (NSE), RMSE-observation standard deviation ratio (RSR) and coefficient of determination (R^2)) evaluated the model performance. The NSE values between 0.51 and 0.83 have been confirmed by calibration and validation for satisfactory and good performances to simulate daily river discharges at 12 gauge-stations. After the model

established, changes in dam water releases during the 2011 floods have been examined as to how the flood peak could be attenuated. Within the dam discharge at the higher amounts of water starting in July, 90 percent of the overflow volume with $3,924 \text{ m}^3/\text{s}$ is damped as the highest flow peak at the origin of the CPR. The result showed that the dam operation plays an essential rule for flood control. Thai Master Plan focusing on detention ponds and retarding basins were assessed impacts on the 2011 flood peak as well. The simulation resulted that these projects could not effectively mitigate the flood. By the combination of dam operation, detention ponds, and retarding basins, 94 percent of overflow volumes could be flattened out.

Chapter 4 aimed to develop the approaches of post-processing d4PDF data based on the CPRB conditions such as topography, climate pattern, available climate data, *etc.* The post-processing of d4PDF data consists of interpolation and bias correction methods. Available climate data at 22 met-stations were successfully interpolated into 57 gridded cells using the Gradient-plus-inverse-distance-squared (GIDS) method. Due to the different patterns between rainfall and temperature, the method of bias correction used for precipitation could not be applied to temperature. In the case of rainfall, bias correction approaches have been developed in terms of time windows: seasonality and month. Dry seasonal datasets were corrected by the gamma distribution approach with setting monthly time window. And, the gamma distribution combined with a Generalized Pareto Distribution (Gamma & GPD) approach with seasonal time window setup applied to rainy season datasets. After the correction, the developed approaches were able to obtain three substantial findings: producing extreme rainfall events, expanding dry days during the dry season, and intensifying rainfall amounts during the rainy season. Regarding the bias correction method for temperature, the Equidistant Cumulative Distribution Function

Matching (EDCDFm) was used to correct maximum and minimum temperatures. The d4PDF temperatures were adjusted in a similar pattern with observation through the EDCDFm method. Future climate d4PDF data of three ensembles (MI, MP, and MR), each comprising 15 members, have been corrected for two periods (2051-2070 and 2090-2110) by the developed approaches. The MI and MP ensembles of corrected rainfall data showed a similar trend for most areas of the CPRB. At the Ping River Basin, a reduction in annual rainfall of about 500-1,000 mm/year was predicted using MI ensemble. Maximum annual rainfall of more than 3,000 mm/year has been projected by all ensembles.

In Chapter 5, since the inappropriate pond construction from the Free Pond Construction Project for non-irrigated areas affected the frequency of pond overflows and water shortage. In order to reduce the frequency, the combination of water requirements model, water budget model, and economic model has been established for the pond management model. Three classified ponds (public, private, and future ponds) were simulated in the pond management model with designed operation rules based on monthly water demands and protection against floods and droughts. After simulations of these three classified ponds, appropriate pond capacities at higher than 80% of pond reliability have been suggested. Public ponds with a depth of 1-4 meters should be constructed in floodplain areas. For existing private ponds, a minimum capacity of 500-3,250 m³ and a maximum capacity of 1,800-3,250 m³ have resulted for reconstruction. And ponds with a range of 2-4 m with capacity over 5,000 m³ were recommended for the future construction. This chapter also determined the numbers of future ponds to avoid insufficient water supply. Approximately 1,000 units of future ponds in each sub-district have been proposed for future construction plans in the non-irrigation areas. In view of the

comparison between maximum and minimum capacities in the economic model, the constructions of the lower number of future ponds with maximum capacity could have more benefits than minimum capacity.

In Chapter 6, the reservoir operation models of Bhumibol Dam and Sirikit Dam have been created by optimized performances using the Adaptive Neuro-Fuzzy Inference System (ANFIS). The forms and numbers of membership functions (MFs) and additional setups have been adjusted to improve the model performances. From the eight forms of MFs, the trapezoidal-shaped membership function showed well performance. Four basic inputs (inflow, storage, rainfall, water demand) and additional monthly input could obtain better performance than seasonality setup. The NSE values of 0.43 and 0.47 were optimized performances to simulate daily reservoir discharges for Bhumibol Dams and Sirikit Dam, respectively. In order to achieve effective reservoir operation for protection against floods, the additional reservoir operation rules were designed by considering the timing and the daily release storage ratios (r). The daily release storage ratios (r) of 0.006 and 0.001 were recommended to control water releases at the mid (July-August) and end (September-October) of rainy seasons, respectively. These ratios were examined by their impacts on river flow, and the results show that the flood peaks could be decreased. In consideration of drought mitigation, the additional operation managed to add an additional water release of about 14 million cubic meters (MCM) for Bhumibol Dam and 7 MCM for Sirikit Dam when the Lower CPRB has no rainfall for over seven days. Finally, future climate change data have been used to predict future discharges of reservoirs. Trends of reservoir releases have shown that about 500-2,000 MCM per month and less than 400 MCM per month of water could be discharged at the mid and end of

rainy seasons, respectively. Approximately 6,000-8,000 MCM would be stored in both dams during the rainy seasons to support water demands for the next dry season.

Chapter 7 aimed to answer the main research question as to how changes in future climate and water resources management affect river discharges. Previous outputs, which were daily climate data from Chapter 4, pond water inflows and releases from Chapter 5, and reservoir discharges from Chapter 6 have been used as an input in the hydrological model established in Chapter 3. Daily river discharges at five gauge-stations located in both Upper and Lower CPRB were predicted for two periods (2051-2070 and 2091-2110). The annual maximum daily flow, the number of days with overflow per year, and the number of days with no flow per year related to non-exceedance probability have been analyzed for flood frequency, overflow duration, and water shortage duration. Flood frequency distributions indicated that flood frequency for the period 2091-2110 was greater than for the period 2051-2070. Through the setups of climate change and reservoir water releases, the annual maximum daily flow could rise up to 6,800 m³/s on the CPR origin. It also resulted that the days with no flow were up to 80 days at downstream of Ping River and mid-stream of CPR. With regard to the impacts of pond management, the flood peaks at the Lower CPRB in 2006 and 2011 could reduce approximately 2,000 m³/s. In view of the combined effects of future climate change, reservoir water releases, and pond management, the annual flow peaks could attenuate at the extreme river discharge at the end of rainy seasons (August-October). A significant finding was that the pond management could mitigate water shortages during low flow periods.

8.2 Recommendations and Future Perspectives

Since information on how to operate the pond and how to manage a pond for long-term use is not provided, the author suggests providing guidelines on pond management in the Thai language based on the results in Chapter 5. In the guidelines, appropriate pond designs and pond operations should be included in order to prevent future overflows and water scarcity. Moreover, the guidelines should provide how farmers and pond owners could get more benefits from pond management, such as increasing agricultural and aquacultural productions, improving water quality, *etc.* In order to apply suggested pond designs for constructions, pros and cons of larger and smaller pond sizes should be discussed in terms of pond purposes, environmental aspects, stakeholder opinions, and government budgets.

Within the results and discussion in Chapter 6, with ANFIS the optimize performances of reservoir operation models for both Bhumibol and Sirikit Dams were unsatisfactory, with the NSE values below 0.5. Numerous models have been constructed to improve model performance by adjusting the forms and numbers of membership functions (MFs) and additional setups. However, too complicated MFs and the setups in the models could not achieve better performance. It could lead to a training period of eight years involving the years with normal discharges, floods, and drought events. The ANFIS may not learn all patterns of the reservoir operations due to the short duration for the training process. Particularly, the underestimated simulation of the daily discharges showed after the 2011 floods, since the special reservoir operations were used to release the high water amount during the 2012 dry season. For the further model construction

using ANFIS, the special operations during and after flood occurrences should be designed as well as the extended training periods up to 30 years.

In Chapter 7, the undesirable impacts of pond management projected the changes in timing and increases in the annual maximum daily flow in the Yom and Nan River Basins. The highest flow peaks in July raised approximately 500 m³/s, which then flows were always higher than their river capacities. Because of this impact, the timing of pond water release at the beginning of rainy seasons (May-July) should be considered in more detail when pond should release water based on the characteristics of flow regime in each sub-basin of Yom and Nan River Basins.

In the perspective of the Thai Government's plan, insufficient river capacity in most areas of the CPRB causes overflow and increases the occurrences in the frequency of floods. Given the results of annual maximum daily flow in Chapter 7, the river capacity should be based on a non-exceedance probability of 0.95 in order to maximize flood protection and minimize overflow frequency in the future. It is recommended that river capacities of 2,500 m³/s, 2,800 m³/s, 2,400 m³/s, 5,200 m³/s, and 3,900 m³/s should be improved at stations Y.17, N.67, P.17, C.2, and C.13, respectively. However, the urbanization is a limitation to increase river capacities at the Lower Chao Phraya River Basin. Artificial canals connected to the delta of Chao Phraya River might be a solution to release water for future floods.