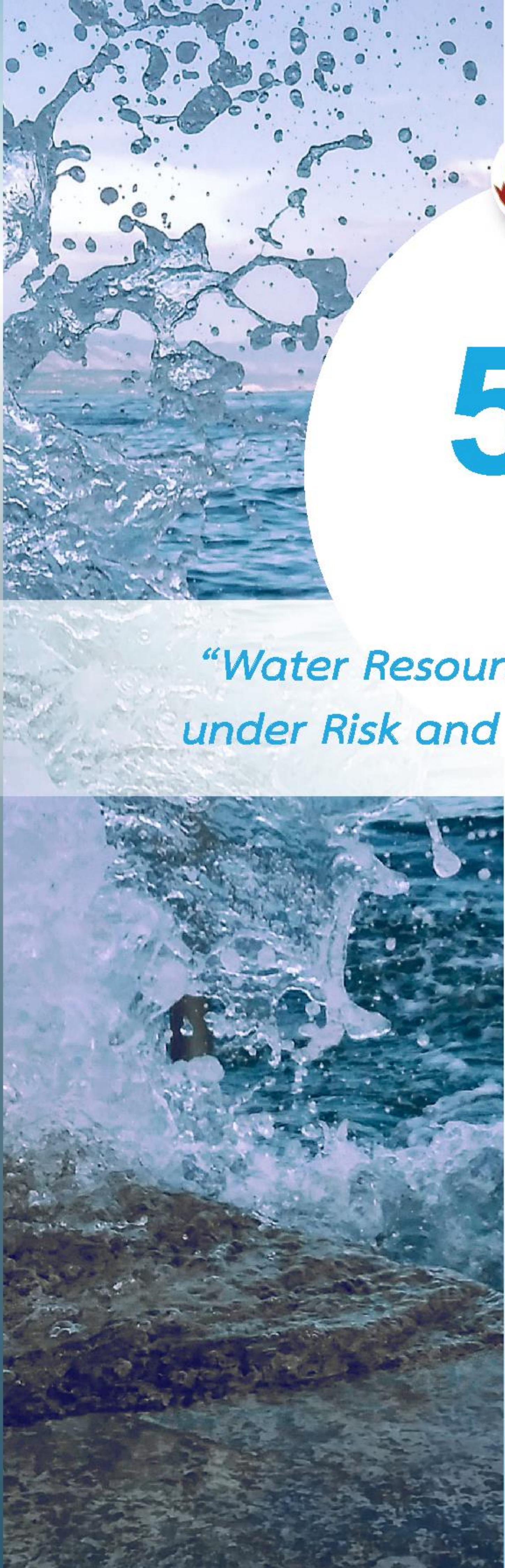

5th International Conference on Water Resources Engineering

"Water Resources Management under Risk and Uncertainty"

Full Paper Proceedings

26 November 2021

Online Conference

FULL PAPER PROCEEDINGS

The 8th National Conference on Water Resources Engineering & The 5th International Conference on Water Resources Engineering

WATER RESOURCES MANAGEMENT UNDER RISK AND UNCERTAINTY

26 NOVEMBER 2021

ORGANIZED BY

DEPARTMENT OF IRRIGATION ENGINEERING, FACULTY OF ENGINEERING AT KAMPHAENG SAEN, KASETSART UNIVERSITY

SUB-COMMITTEE ON WATER RESOURCES ENGINEERING UNDER THE ENGINEERING INSTITUTION OF THAILAND

IRRIGATION ENGINEERING ALUMNI ASSOCIATION UNDER H.M. THE KING'S PATRONAGE

IRRIGATION COLLEGE

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MESSAGE FROM THE DEAN OF THE FACULTY OF ENGINEERING AT KAMPHAENG SAEN, KASETSART UNIVERSITY

The 8th National and 5th International Conference on Water Resource Engineering under the topic "Water Resource Management under Risk and Uncertainty" were academic conferences organized by the cooperation between the Engineering Institute of Thailand under HM the King's Patronage; Faculty of Engineering at Kamphaeng Saen, Department of Irrigation Engineering, Kasetsart University; Irrigation College; Engineering Alumni Association under H.M. the King's Patronage. This conference aims to provide a great opportunity for both national and international researchers, and general people to participate and exchange their knowledge and experiences for enhancing and improving water management practices in the future.

It is an honor to host the 8th National and 5th International Conference on Water Resource Engineering. As the chairman of the committee for organizing, I would like to express my sincere appreciation to all authors for their contributions to this conference. Also, I would like to thank all the organizing committees, the technical committees, the public agencies, and the private agencies for their excellent support. Also, I sincerely hope that everyone will benefit from this academic conference.

Assoc. Prof. Dr. Chouw Inprasit

Dean of the Faculty of Engineering at Kamphaeng Saen

Kasetsart University

MESSAGE FROM THE PRESIDENT OF THE IRRIGATION ENGINEERING ALUMNI ASSOCIATION UNDER THE ROYAL PATRONAGE

The National Water Resources Engineering Conference is considered as another national forum that allows academics, researcher, teachers and education personnel, students, and engineers from various organizations to demonstrate their potential through presentations that have been assured the quality by qualified persons as the Irrigation Engineering Alumni Association under the Royal Patronage, the organization aims to be the center of the relationship among the members, promote education and dissemination of science. Right now, it is time to be grateful and welcomes the Subcommittee of Water Resources Engineering, Engineering of Thailand under the Royal Patronage of Thailand, Department of Irrigation Engineering, Faculty of Engineering, Kasetsart University, Kamphaeng Saen and College of Irrigation Department of Irrigation, Associate Institute, Kasetsart University, which co-hosted the 8th National Water Resources Engineering Conference.

Irrigation engineering and water resources are the basis of everything, especially driving both agricultural and industrial economies. However, changing the context of society from an agricultural society to an industrial society, climate change and the risk of flooding and drought has put Thailand's water management under risk and uncertainty. Therefore, irrigation science and water resources have become the cornerstone to ensure efficient, appropriate, and equitable water management.

On behalf of the Irrigation Engineering Alumni Association under the Royal Patronage. Hopefully, this symposium will achieve its objectives and strengthen the network of irrigation science and water resources for the benefit of Thailand hereafter.

Dr. Thongplaew Kongchang
Deputy Chief, Ministry of Agriculture and Cooperatives
President of Irrigation Engineering Alumni Association
under the Royal Patronage

MESSAGE FROM THE DIRECTOR OF IRRIGATION COLLEGE

Irrigation college of Royal Irrigation Department (RID), affiliated to Kasetsart University is celebrating its 84th year of our on-going commitments to educate and promote expertise in irrigation and water engineering. Irrigation College also aimed to support scholarly academic events to advance our research and teaching in sustainable ways including being part of this 8th National Water Resources Engineering Conference which provide opportunity to build more academic collaborations. This conference also offers the expansion of irrigation and water resources academic networks ranged from domestic to international via their qualified academic work presentations and publications to generate more knowledge exchanges. This conference is also organized in response to Thailand's water resource management under climate change risks and uncertainties. Consequently, the integration of academic knowledge with practical in field experiences were taking place to modernize technologies toward more responsive and informative overall decisions makings starting from pre-incident to post-incident stages.

Irrigation College would like to thank you and acknowledge the Department of Irrigation Engineering, Faculty of Engineering, Kamphaeng Saen, Kasetsart University, the Subcommittee on Water Resources Engineering, and the Engineering Institute of Thailand Under H.M. The King's Patronage, for allowing Irrigation College to take part of this academic conference which we aimed to cooperate and comply academically with our full efforts.

Chaiya Phoungphotisop

Director of Irrigation College

Royal Irrigation Department, Pak Kret

MESSAGE FROM THE PRESIDENT OF THE ENGINEERING INSTITUTE OF THAILAND UNDER H.M. THE KING'S PATRONAGE

Water is vital for life. Human beings use water directly, in their daily lives, and indirectly, e.g., in agriculture, industry, transport, etc. Water is a reusable resource but climate change in various countries, including Thailand, is leading to floods, drought and other problems. Many factors will lead to unavoidable damage, either naturally or from the management of water and other resources, if management of them is not good enough.

The Engineering Institute of Thailand under H.M. The King's Patronage in collaboration with educational institutions, including government and private agencies, have organized the 8th National and 5th International Conference on Water Resource Engineering, under the theme “Water Resource Management under Risk and Uncertainty”. It will serve as a forum for academics, researchers, students and operators concerned in water resource engineering in both the public and private sectors across the country to exchange knowledge, experience and ideas, relating to research, professional expertise and state-of-the-art modern technology transfer.

This conference has been organized successfully because of the cooperation and support of numerous parties. I would like to take this opportunity to express my sincere thanks to the Sub-committee on Water Resource Engineering, the Engineering Institute of Thailand under HM the King's Patronage (EIT); the Faculty of Engineering at Kamphaeng Saen, Department of Irrigation Engineering, Kasetsart University; Irrigation College; Irrigation Engineering Alumni Association under H.M. The King's Patronage; and all parties of the Central Organizing Committee, who devoted time to the conference to enable it to achieve its objectives, as well as the public and private sectors, whose support makes it successful. The conference will help to develop the professional field of water resource engineering, and to make progress and benefit society in the future.

Dr. Thanes Weerasiri

President of The Engineering Institute of Thailand

under H.M. The King's Patronage

MESSAGE FROM THE CHAIRMAN OF THE SUB-COMMITTEE ON WATER RESOURCE ENGINEERING, THE ENGINEERING INSTITUTE OF THAILAND UNDER HM THE KING'S PATRONAGE (EIT)

The Sub-committee on Water Resource Engineering by the Engineering Institute of Thailand under HM the King's Patronage (EIT) was established with the objectives of providing academic services to meet EIT’s goals and regulations, and focusing on the development, promotion and support of the water resource engineering profession to further enhance its progress in Thailand.

The 2021 Sub-committee on Water Resource Engineering has a one-year term. On the whole, its policies and action plans emphasize academic affairs.

The 8th National and 5th International Conference on Water Resource Engineering – “Water Resource Management under Risk and Uncertainty” – have taken the combined efforts of local and international academics, water engineering operators and students, who have shared their knowledge and experience, and presented their research, which benefits those concerned, including those interested in water resources. The conference would not be possible without the cooperation of all relevant parties, for example, the 2021 advisory and sub-committee members; the Central Committee for Organizing the 8th National and 5th International Conference on Water Resource Engineering; the Faculty of Engineering at Kamphaeng Saen, Department of Irrigation Engineering, Kasetsart University; Irrigation College; Irrigation Engineering Alumni Association under H.M. The King's Patronage; and public and private agencies; as well as the companies who provided budgetary support, coordination and other operations to enable it to be carried out successfully. Finally, I would like to thank all parties concerned for supporting the smooth operation of the 2021 Sub-committee on Water Resource Engineering and the Central Committee for Organizing the 8th National Conference and 5th International Conference on Water Resource Engineering.

Last but not least, I do hope that the conference participants will gain benefits in accord with their expectations.

Dr. Kasem Pinthong

Chairman of the Sub-committee on Water Resource Engineering,
the Engineering Institute of Thailand under HM the King's Patronage

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Conference Program

The 8th National Conference on Water Resources Engineering
&
The 5th International Conference on Water Resources Engineering
November 26, 2021

Opening Ceremony	
09.00-09.30	**Welcome Remark** by **Dr. Kasem Pinthong** Chair of the sub-committee on water resources engineering under the Engineering Institute of Thailand under H.M. The King's Patronage by **Assistant Professor Dr. Thanes Weerasiri** President, The Engineering Institute of Thailand under H.M. The King's Patronage
	Opening Remark by **Associate Professor Dr. Chow Inprasit** Dean of Faculty of Engineering at Kamphaengsaen campus Kasetsart University
Keynote Address	
9.30-10.00	Keynote address I **Mr. Lalit Thanomsing** Secretary-General of the Office of the Royal Development Projects Board
10.00-10.30	Keynote address II **Dr. Surasri Kidtimonton** Secretary-General of the Office of the National Water Resources
10.30-11.30	Keynote address III **Professor Gary P. Merkley** Senior Supervising Engineer Natural Resources Consulting Engineers, Inc. California, US.
Parallel Sessions	
13.00-16.00	**International conference :** Session 1: Water Management / Water Quality Management and Ecosystem Session 2: Meteo-Hydrological and Climate Change / Water Supply and Sanitary / Risk and Disaster /Hydroinformatics
	National conference: Session 1:Water management, meteo-hydrological and climate change Session 2: Irrigation and Drainage Session 3: Water Quality and water supply engineering Session 4: Emerging technology and decision support
16.00-16.30	**Closing Remark**

LIST OF ARTICLES PUBLISHED IN JOURNALS

FAST TRACK: MAHASARAKHAM INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY

CC6 ASSESSMENT OF ROYAL RAINMAKING PERFORMANCE WITH GROUND-BASED RAINFALL IN PHETCHABURI RIVER BASIN

RD3 CATCHMENT-SCALE FLOOD HAZARD MAPPING IN THE LOWER AREAS OF LAM PAO RIVER BASIN, THAILAND

WQ1 SIMULATION OF WATER LOSSES FOR THE 1D SALINITY FORECASTING MODEL IN CHAO PHRAYA RIVER

NORMAL TRACK: NARESUAN UNIVERSITY ENGINEERING JOURNAL

WM7 LOW-FLOW ASSESSMENT FOR UNGAUGED SUB-BASINS IN THE UPPER PING RIVER BASIN, THAILAND

WM15 EVALUATING HYDROELECTRICITY PRODUCTION RE–OPERATING WITH ADAPTED RULE CURVE UNDER CLIMATE CHANGE SCENARIOS CASE STUDY OF BHUMIBOL DAM IN THAILAND

WM21 TRACING CROP WATER REQUIREMENT IN THE PUMPING, GRAVITATIONAL AND INUNDATION IRRIGATION SCHEMES OF THE GREATER CHAO PHRAYA RIVER BASIN USING CLOUD-BASED IRRISAT APPLICATION

RD0 DEVELOPMENT OF A WEB-BASED INTERFACE FOR URBAN FLOOD WARNING SYSTEM IN BANGKOK, THAILAND

RD7 DROUGHT ANALYSIS IN THE EASTERN ECONOMIC CORRIDOR BY USING THE STANDARDIZED PRECIPITATION INDEX (SPI)

WQ2 WQI INDEX ASSESSMENT OF RAW WATER FOR WATER SUPPLY

Water Management

BMA FLOOD MITIGATION IN RESILIENCE PERSPECTIVE OF FLOOD VULNERABILITY INDEX

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ABSTRACT

Bangkok flooding results from the rain in the area, even if the intensity is less than the design value. It affects populations in different districts with varying degrees of severity, depending on several factors. To address this obstacle, the Flood Vulnerability Index (FVI) method, in which the main parameters consist of Exposure (E), Susceptibility (S), and Resilience (R), was analyzed and implemented. The higher FVI means more inundation risk in the area. On the other hand, the reducing values of E and S or increasing R can generate lower FVI. This study tested the mitigation concerning resilience perspective in seven Bangkok areas, dividing the physical characteristics into three groups according to drainage system performance. The sensitivity analysis of FVI concerning the R parameter by the factor changes of retention pond to the area ratio (P/A) was tested. The FVI analysis using the Fuzzy Inference technique was used in this study. The simulated results showed that the existing conditions of those seven districts have FVI values between 0.60 and 0.90 approximately. After increasing parameter R according to the feasible physical conditions of the areas, it was found that the FVI of Chatuchak, Bangkhen, and Khanna Yao districts could be reduced to 0.70 approximately, while at the Phayathai and Ratchathewi districts could not be reduced due to the limited conditions of residential.

On the other hand, business areas in Bangkhuntien and Prawet districts could not be reduced due to the limited conditions of Pond area ratio with an existing condition. The current condition is already tremendous; adding pond storage could not reduce FVI. Therefore, other measures such as warning systems or groundwater storage in a resilience perspective should be considered in these two districts.

Keywords: Bangkok Metropolitan Administration (BMA), Flood Mitigation, Flood Vulnerability Index (FVI)

1. INTRODUCTION

Bangkok is located at the end of the Chao Phraya River Basin before reaching the Gulf of Thailand. The flood events in Bangkok are usually caused by heavy rainfall and the rise in water level in the Chao Phraya River due to large flow from the North part of Thailand. In the past, most of the occurrence of heavy rains in Bangkok resulted in severe flooding. Bangkok is a lowland area with a slight slope. The average level is approximately 0.00 to +1.50 meters above mean sea level (m. MSL, [1]) below the water level in the Chao Phraya River and is an area affected by tidal. Due to the physical of the area, the drainage from the gravity flow cannot flow into the Chao Phraya River at full efficiency. Moreover, with the limitation of the area, it is difficult to expand the sewer system, and some areas have problems with encroaching along the canal. Drainage using a pump is therefore imperative. However, with the limitation of the drainage system, it is not easy to manage the whole system. Thus, Bangkok Metropolitan Administration (BMA) has divided water management into sub-polder systems, 22 polders in each sub-polder system, and drainage systems have been improved before draining to the canal and Chao Phraya river next. However, the management of each sub-polder system was still ineffective due to the problem of the canal system connected to the sub-polder system as mentioned above. With such issues in the past, Bangkok Metropolitan Administration has continuously implemented projects to increase drainage efficiency. In addition, it is also preparing a plan to prevent and solve flooding problems in the Bangkok area in 2021. Consisting of 6,564 km of sewer line, 2050 km of main and 4,514 km of sub sewer line, and constructing a pumping system capable of the total drainage capacity is approximately 2,468 cu.m/s.

Moreover, the pumping station installed along the Chao Phraya River has a drainage capacity of approximately 1,087 cum/s. In addition, drainage tunnels are being built to solve the problem of drainage. In addition, before the rainy season, the BMA has prepared to include inspecting the drainage system, drainage tunnel, pumping stations, and pumping wells and reducing the water level in the canal to the standard to prepare for the amount of rainfall. Bangkok has completed several projects to optimize drainage systems. However, even if measures are taken together with the budget for using structures to solve flooding, there are still problems. Bangkok has spent much budget on this part, as mentioned above. However, when there is rain which the intensity is less than the design intensity of 77 mm/hr, in a short time, there is still flooding.

Flood Vulnerability Index (FVI), adapting by the method of Balica (2012)[2], defines the vulnerability by the FVI = (E*S)/R. The equation represents exposure and susceptibility increase the flood vulnerability index. The exposure (E) parameters consist of land use, topography /slope, rainfall, flood duration, population density, etc. The susceptibility parameters (S) consist of urban growth, quality of infrastructure, human health, frequency of flood occurrence, etc. The resilience parameters (R) consist of a warning system, emergency service, past experience, flood management/dike, pond storage.

Another assessment sample is by P. Shray et al. (2020)[3], Social-economic and environmental assessment of urban sub-catchment flood risk using a multi-criteria approach: A case study in Mumbai City, India. This study presented a comprehensive and integrative approach to analyze flood risks and to support the identification and prioritization of interventions to mitigate these risks at the urban sub-catchment level, to assess on a fuzzy technique system methods based on social, economic, environmental, infrastructure criteria were used to analyze flood risk in four Indian cities.

This study considers the Resilience (R) value to test for reducing the FVI value. This study uses Pond Storage Area as a parameter in resilience to test. According to the data from the Drainage and sewer department, it is found that there is currently a total pond storage area of 32 locations, distributed throughout the area with a total capacity of about 13 million cubic meters. It is expected that this year 2021 will add approximately 40 billion cubic meters of Pond Storage Area in BMA[3]. This study analysis of FVI concerning R parameter by the factor changes of retention pond to the area ratio (P/A) was tested. It will support the policymakers in identifying risk areas. To create awareness and adaptation of people who have to live during the flood draining and for responsible agencies to use it as an index determining working policies or even budgets. Udnoon, 2020[4] found that most areas in Bangkok, especially the east and the west, are high risk as FVI range from 0.6 – 0.8 and 0.4 – 0.7, respectively, as shown in Figure 1.

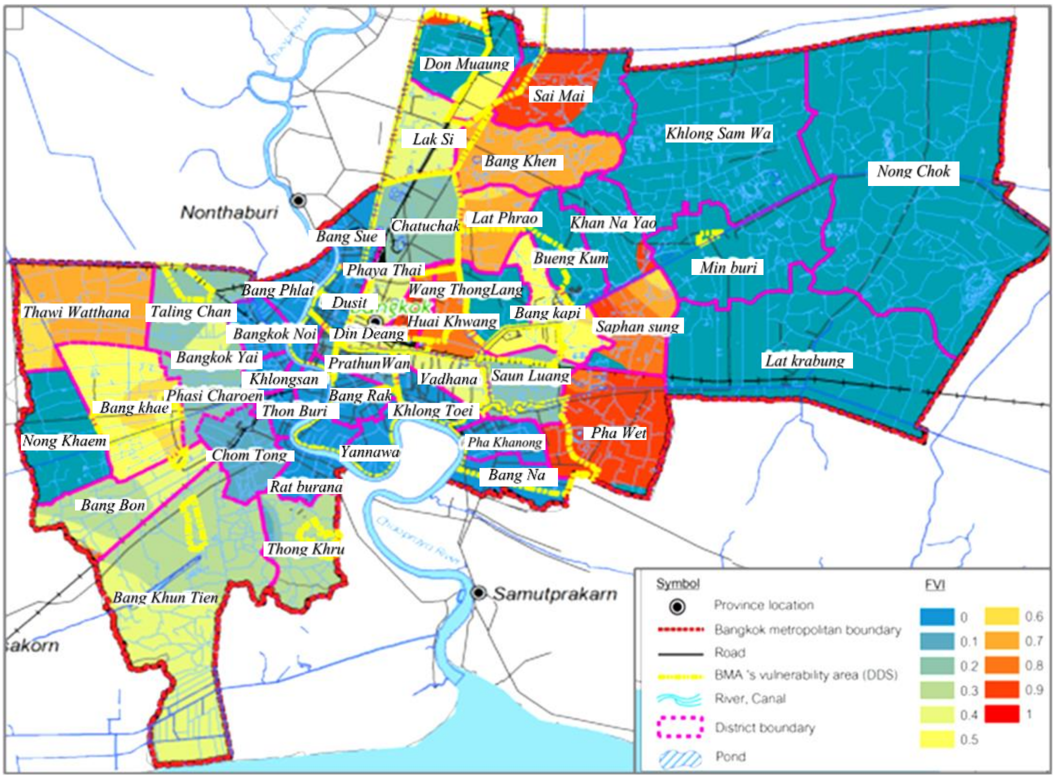


Figure 1 FVI Map of BMA (Udnoon et al., 2020)[4]

According to Figure 1 developed by Udnoon (2020)[4], This study assessed the flood vulnerability approach as a part of flood risk management and FVI technique. The Flood Vulnerability Index (FVI) value < 0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8, and 0.8-1.0 indicate very small, small, medium, high, and very high vulnerability to floods. The study results using FVI indices mostly comply (approximate 70 % of recorded areas) with the occurred situations. The high and very high FVI are found in Bangkok's central east areas, such as Saimai, Bangkhen, Latprao, Wangthonglang, and Dindaeng districts. The moderate FVI is found in the western areas of Bangkok, such as Thawiwattana, Bangkhae, Bangbon, and Bangkhunthien districts.

2. STUDY AREA

In this study, the mitigation concerning the resilience perspective has been tested in seven areas where the FVI values range from high to very high, 0.5-0.8. These areas are categorized into three groups, according to drainage system performance evaluated by Udnoon (2020)[4], as shown in Figure 2 and Table 1.

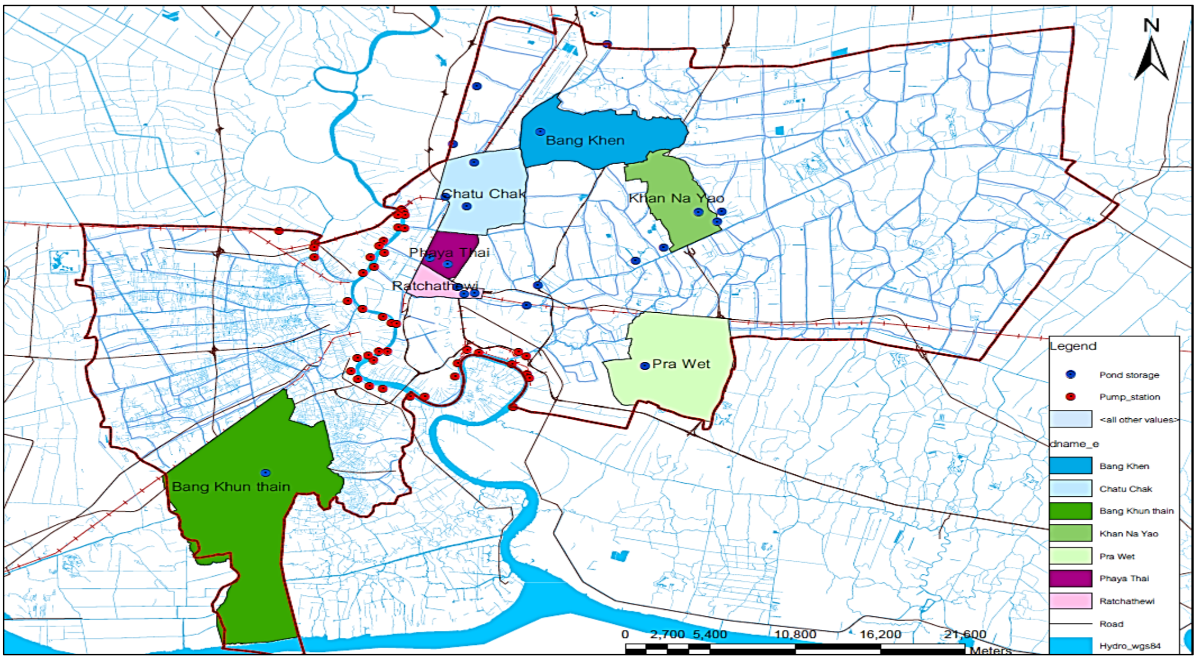


Figure 2 Study area

(i) *Low drainage system performance (25%)*: Chatuchak and Bangkhen districts, the central east areas of Bangkok, are the densely populated areas in which the population are 6,287 and 6,081 person/Sq.km., respectively. The physical characteristics of both districts are a high ratio of impervious area, with 25% of drainage system performance, and the pond area ratio is 0.007 and 0.008, respectively.

(ii) *Medium drainage system performance (50%)*: Bangkhuntien, Prawet, and Khannayao districts, the west areas of Bangkok, which the population are moderate dense; 1,914, 4,213, and 4,886 person/Sq.km., respectively. The physical characteristics are in a medium impervious ratio, with 50% drainage system performance, and the pond area ratio is 0.049, 0.093, and 0.009, respectively. In addition, the Bangkhunthien district has the potential to increase the pond area.

(iii) Good drainage system performance (75%): Phayathai and Ratchathewi districts, the central areas of Bangkok, which the population are very dense; 10,293 and 13,121 person/Sq.km. The pond area ratio is 0.015 and 0.041, respectively, and the drainage system performance is 75%.

Table 1 Physical Characteristics of the Study areas

District	Drainage system	Pond storage	Area	Ratio Pond/Area
	Performance (%)	(cu.m.)	(Sq.m.)	(Cu.m/Sq.m.)
Chatuchak	25	288,000	40,959,096	0.007
Bangkhen	25	253,000	32,656,716	0.008
Bangkhuntien	50	6,000,000	122,207,808	0.049
Prawet	50	5,000,000	53,728,764	0.093
KhannaYao	50	228,000	25,380,514	0.009
Phayathai	75	142,000	9,214,668	0.015
Ratchathewi	75	297,150	7,167,652	0.041
Source	(Udnoon,2020)	Department of Drainage and Sewerage	Department of Drainage and Sewerage	

3. METHODOLOGY

This study aims to determine the variables that could decrease the flood vulnerability index (FVI) of the studied area. From the equation developed by Balica [5], FVI = (E*S)/R; thus, an increase in Resilience (R) parameters results in a decrease of FVI. The Resilience(R) parameters using pond area ratio (PA) variables, which are grouped by drainage system performance (DE) and fix rainfall data, which is a 5-year return period intensity (76 mm/hr). Each variable is divided into levels, i.e. (PA) divided into low, medium, high, and very high. (DE) is divided into bad, medium, good, very good. The sensitivity analysis was conducted using the Fuzzy of MathLab technique to assess the flood vulnerability index. The pond area ratio has been increased based on the existing condition, from 5%, 10%, 15%, 20%, 30%, and 50%, then the FVIs are evaluated, as the steps shown in Figure 3

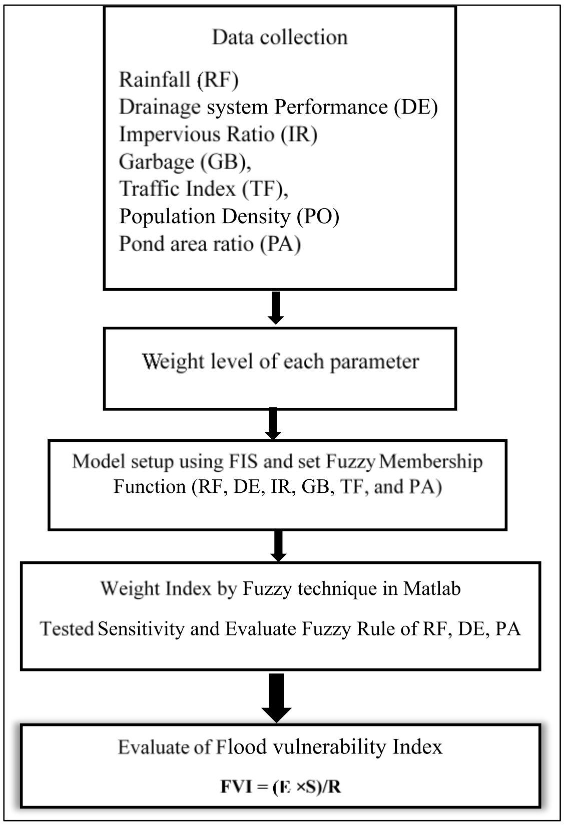


Figure 3 Method of the study

3.1 Method of the study

From Figure 3, the method can be described a follows.

(i) Data collection

The data that has been collected is listed in Table 2.

Table 2 Collected Data

Data	Source
Rainfall Intensity (RF)	Thai Meteorological Department's(TMD),2016[4]
Drainage system performance(DE)	Drainage and Sewer Department (DSS), 2016[1]
Impervious ratio (IR)	Department of Public Works and Town & Country Planning, Thailand, 2006[4]
Garbage (GB)	The Pollution Control Department, 2008[4]
Traffic Index (TF)	The Bureau of traffic safety, 2019[4]
Population density (PO)	Department of Public Works and Town & Country Planning, Thailand, 2006[4]
Pond area ratio (PA)	Drainage and Sewer Department (DSS), 2021[1]

(ii) Weight level of each parameter

Rainfall Intensity (RF) is defined as Light <= 0.5 mm/hr., Moderate 5.1-25 mm/hr., Heavy 25.1-50 mm/hr., and Very Heavy >=50.1 mm/hr.

The Drainage System Performance (%), DE is defined as bad 0-25, medium 25-50, good 50-75, and very good 75-100.

Impervious ratio (IR) is defined as Light <= 0.5 mm/hr., Moderate 5.1-25 mm/hr., Heavy 25.1-50 mm/hr., and Very Heavy >=50.1 mm/hr.

Garbage (GB) is defined as Bad > 80%, Medium 70%, Good 60%, and Very good 100%

Traffic Index (TF) is defined as a level of service A-F is 0-1, respectively.

Population density (PO) is defined as low <=1/100, medium 1/100-1/75, high 1/75-1/50, and very high >1/50.

(iii) Model setup and Fuzzy Membership Setting

The fuzzy logic is also an effective tool for risk assessment and analysis. Several scientists have used fuzzy logic for risk assessment in different areas. [6] in proposed fuzzy concepts, such as fuzzification, membership functions, aggregation, defuzzification, size of parameters, the effect of parameters, membership level, fuzzy sets, intersection of two variables, a maximum of two variables, and a minimum of two variables for the first time in structural engineering.

The assessment of vulnerability through its fuzzy nature remains an ill-structured problem. This study attempts to assess the FVI by applying the Fuzzy Logic Toolbox with MATLAB, in which the FIS workflow is shown in Figure. 4

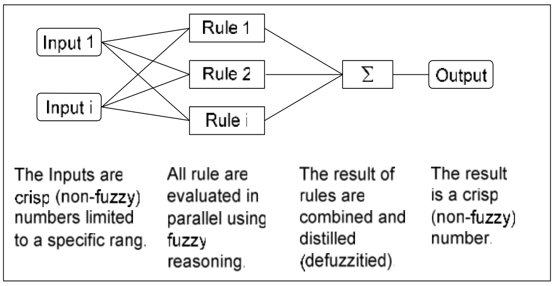


Figure 4 Fuzzy Inference System Work Flow
Source: Fuzzy Logic Toolbox in MATLAB [7]

The membership (MF) that was set up by Udnoon (2020)[4], using Fuzzy Logic Toolbox with MATLAB, is shown in Figures 5(a)-5(f), and the membership of Pond Area Ratio is shown in Figure 5(g).

(a) Drainage System Performance (%), (DE) was defined as service life, land subsidence condition, pipe sag, dredging frequency. It is defined as bad 0-25, medium 25-50, good 50-75, and very good 75-100. Refer to the Drainage and Sewer Department (DSS)[1], as shown in Figure 5(a).

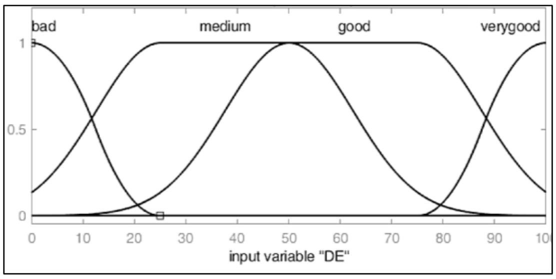


Figure 5(a) MF of Drainage System Performance (DE), [1]

(b) Rainfall Intensity (RF) was defined based on the rain intensity in an hour. It is defined as Light <= 0.5 mm/hr., Moderate 5.1-25 mm/hr., Heavy 25.1-50 mm/hr., and Very Heavy >=50.1 mm/hr. Refer to the Thai Meteorological Department's (TMD), 2016, as shown in Figure 5(b).

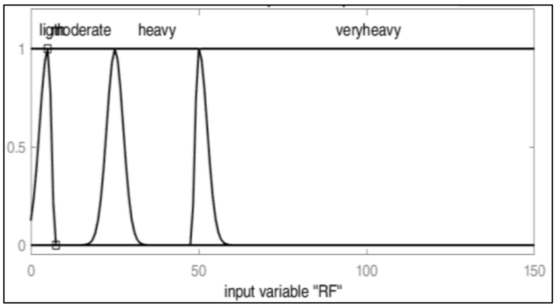


Figure 5(b) MF of Rainfall (RF)

(c) Impervious Ratio (%) (IR) was defined based on the impervious ratio proportion of the residential area, community, department, commerce, and road from land-use to total area. It is defined as Bad >= 80%, Medium 70-80, Good 60-70%, Very good <=50%. Refer to the Department of Public Works and Town & Country Planning, Thailand, 2006 as Figure 5(c).

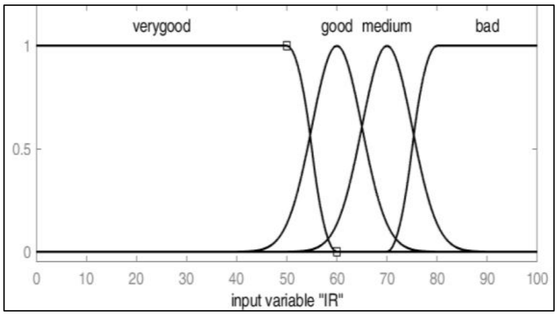


Figure 5(c) MF of Impervious Ratio (IR)

(d) Garbage (%) (GB) was defined based on the amount of waste collected to the total amount of waste. It is defined as Bad > 80%, Medium 70%, Good 60%, and Very good 100%. Refer to the Pollution Control Department, 2008 as shown in Figure 5(d).

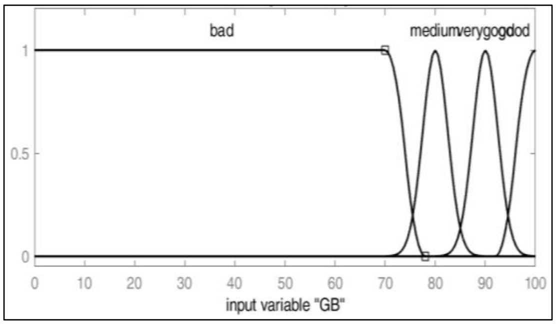


Figure 5(d) MF of Garbage (GB)

(e) Traffic Index (TF) was defined based on the traffic volume in congested hours on the road to the capacity of the highway road. It is defined as the level of service A-F is 0-1, respectively. Refer to the Bureau of traffic safety, 2019, as shown in Figure 5(e).

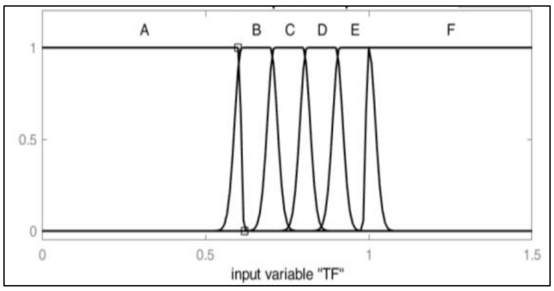


Figure 5(e) MF of Traffic Index (TF)

(f) Population Density (PO), was defined as the population to total area. It is defined as thinly 6,250 – 12,500 (persons/sq.km.), intermediate 12,500 – 25,000 (persons/sq.km.), densely 25,000 – 50,000 (persons/sq.km.), and very densely 50,000 – 75,000 (persons/sq.km.). refer to Refer to the Department of Public Works and Town & Country Planning, Thailand, 2006 as shown in Figure 5(f).

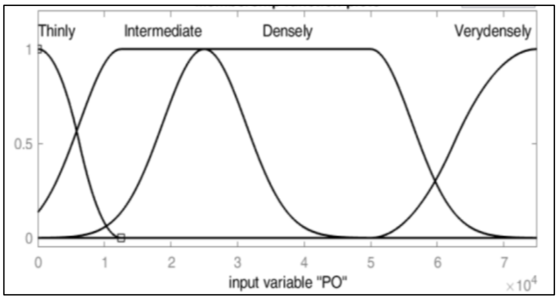


Figure 5(f) MF of Population Density (PO)

(g) Pond Area Ratio, PA, was defined pond storage and area, the storage in the proportion of not less than 1 m^3 per 50 m^2 of land area for providing a water storage area to prevent flooding. It is defined as low <=1/100, medium 1/100-1/75, high 1/75-1/50, and very high >1/50. Refer to the Department of Public Works and Town & Country Planning, Thailand (DPT) defines as shown in Figure 5(g).

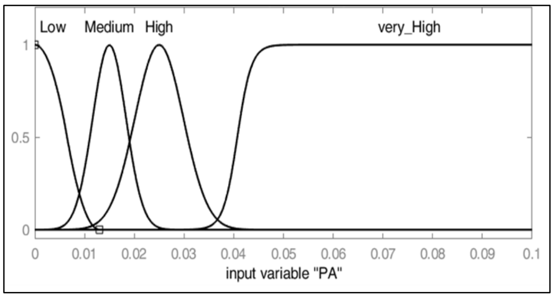
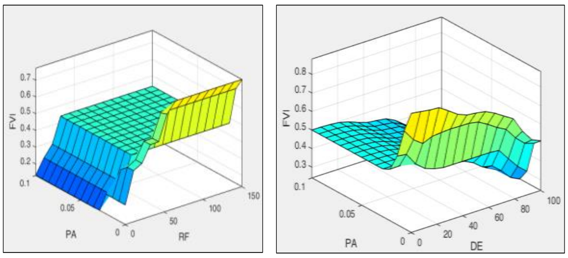


Figure 5(g) MF of pond area ratio (PA)

(iv) The Sensitivity analysis in resilience perspective

The sensitivity test was performed using rainfall intensity of 5-year return period which is 76mm/hr with varying Pond Area ratio (PA) and Drainage System Performance (DE) factors. The Flood Vulnerability Index (FVI) of each district has changed in different. The sensitivity of the parameter is shown in Figure 6. It indicates that (a) increasing (%) pond area ratio affected the FVI values of Chatuchak, Bangkhen, Phayathai, Ratchathewi, and Khannayao districts, and (b) Bangkhuntien and Prawet districts; the FVI will decrease initially, but when increasing (%) pond area ratio above 50%, FVI values will not decrease. The parameter sensitivity test is shown in Figure. 7



(a) RF and PA (b) DE and PA

Figure 6 Sensitivity of parameter in Fuzzy Inference System

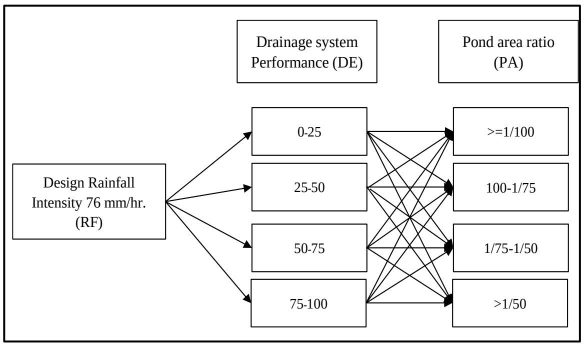


Figure 7 Sensitivity analysis of PA

(v) Evaluate of Flood vulnerability Index

The general formula for FVI is calculated by classifying the components into three groups of indicators, namely, exposure, susceptibility, and resilience (Balica et al.) [5]. The FVI general formula is presented in Eq.1.

$$FVI = \frac{E \times S}{R} \quad (1)$$

where E = Exposure
S = Susceptibility
R = resilience

FVI of each area reflects the exposure, susceptibility, and resilience of that area to acclimate from the effects of those conditions [8]. Exposure is the scope of human settlements and people's lives in flood risk areas [9]. Susceptibility is the system's exposed factor, which affects the probabilities of being harmed during floods (UNESCO-IHE, 2013)[8]. Finally, resilience is the adaptation capacity of each community to changes in a hazardous area by modifying it to achieve an acceptable structural and functional level[10]. With these indicators, additional information can be provided for vulnerability reduction.

The FVI equation developed under exposure, susceptibility, and resilience parameters indicates that a decrease in resilience parameters decreases the FVI values. This concept has been tested in the study area as the pond storage capacity represents the resilience parameters.

These concepts help the engineers with risk analysis. Vulnerability is embedded into the concept of risk[9] in the following Eq.2.

$$\text{Risk} = \text{Vulnerability} \times \text{Hazard} \qquad (2)$$

Resilience assessment is an analysis of the urban system looking at the pond area ratio. Each dimension contributes to the evaluation of the flood vulnerability index for the particular urban system. The membership is constructed in a fuzzy inference system where the RF design rainfall is 76 mm/hr, under the existing drainage system performance, DE [4], pond area ratio, PA, refer to Department of Public Works and Town & Country Planning definition, are set as the primary variables.

3.2 Description of the Flood Vulnerability Index

The flood vulnerability index (FVI) can be used in action plans to manage floods and improve local decision-making practices with appropriate measures to reduce vulnerability in different spatial levels (Balica et al., 2012)[5]. The Index should be designed to produce information for specific areas. The description of the FVI, which the value range from 0 to 1, is shown in Table 3.

Table 3 Flood Vulnerability Index (FVI)

Designation	Index value	Description
Very small vulnerability	<= 0.1	Very small Vulnerability to floods
Small vulnerability	0.10-0.25	Small vulnerability to floods
Vulnerability	0.25-0.50	Vulnerability to floods The measure should be taken to reduce the vulnerability
High vulnerability	0.50-0.75	High vulnerability to floods The measure should be taken with action plans to manage floods to reduce risks
Very high vulnerability	0.75-0.10	Very high vulnerability to floods The measure should be taken with the structure to manage flood to reduce risks

Source: developed from Balica (2012) [5]

4. RESULTS

The Resilience Perspective of the flood vulnerability index (FVI) was calculated for seven areas of BMA, i.e., Chatuchak, Bangkhen, Bangkhuntien, Prawet, Khannayao, Phayathai, and Ratchathewi district, as shown in Table 4.

Table 4 Flood Vulnerability Index (FVI) of the study areas

District	Drainage system Performance (%)	Flood Vulnerability Index (FVI)						
		Existing	Increase Pond Area Ratio					
			5%	10%	15%	20%	30%	50%
Chatuchak	25	0.859	0.843	0.829	0.807	0.790	0.751	0.705
Bangkhen	25	0.813	0.807	0.785	0.761	0.742	0.714	0.691
Bangkhuntien	50	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Prawet	50	0.500	0.500	0.500	0.500	0.500	0.500	0.500
KhannaYao	50	0.756	0.737	0.719	0.709	0.699	0.691	0.688
Phayathai	75	0.688	0.688	0.688	0.688	0.688	0.688	0.688
Ratchathewi	75	0.501	0.500	0.500	0.500	0.500	0.500	0.500

The physical characteristics of the study areas are divided into three groups according to the drainage system performance; (i) the drainage system performance (DE) 25% is Chatuchak and Bangkhen districts, (ii) the drainage system performance 50% is Bangkhuntien, Prawet, and Khannayao districts, and (iii) the drainage system performance 75% is Phayathai and Ratchathewi districts, as shown in Figure 8 to Figure 10.

(i) The drainage system performance (DE) of 25% is Chatuchak and Bangkhen districts. The FVIs presented in Figure 8 indicate that when the pond area ratio is increased up to 50%, the FVI decreases by approximately 15-18%. However, to reduce more FVI values, it may be necessary to improve the drainage system.

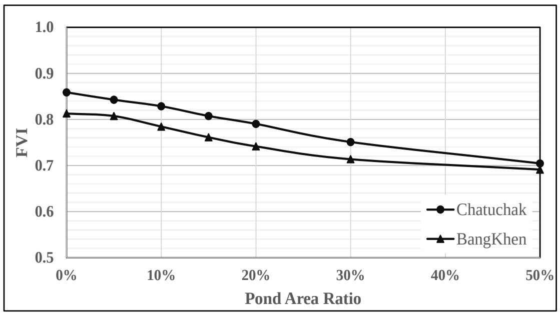


Figure 8 FVI of Chatuchak and Bangkhen districts

(ii) The drainage system performance (DE) of 50% is Bangkhuntien, Prawet, and Khannayao districts. The FVIs shown in Fig. 9 show that an increase of 50% of the pond area ratio had an insignificant effect on the FVI value. To reduce FVI, additional measures such as improving drainage system efficiency may be required.

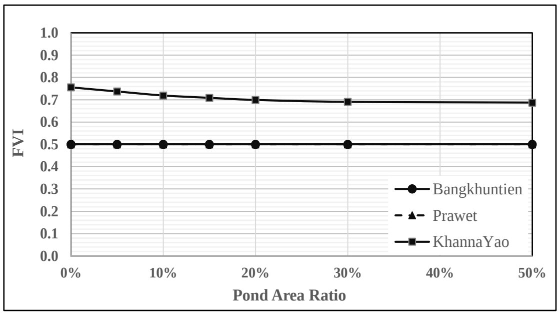


Figure 9 FVI of Bangkhuntien, Prawet, and Khannayao districts

(iii) The drainage system performance (DE) of 75% is Phayathai and Ratchathewi districts. The FVIs shown in Figure 10 indicate that the increased pond ratio did not affect the FVI. However, to reduce the FVI value, additional measures such as a warning system improvement may be required.

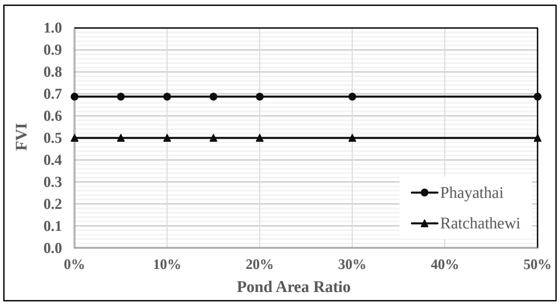


Figure 10 FVI of Phayathai and Ratchathewi districts

The relationship of FVI value with (%) pond area Ratio of each area is shown in Figure 11. It was found that when PA ratio increases, it results in a lower FVI value in most study areas. For example, in Chatuchak, Bangkhen, and Khannayao districts, when (%) pond area ratio increases to 5% 10% 15% 20% 30% 50% respectively, the Flood vulnerability index (FVI) value of those areas will decrease to 18,15, and 10 % respectively. On the other hand, in Bangkhuntien and Prawet, Phayathai, and Ratchathewi, where there is already a high (%) Pond area Ratio and a lot of Drainage system performance (DE), the FVI value did not decrease when compared to the increase in (%) pond area ratio.

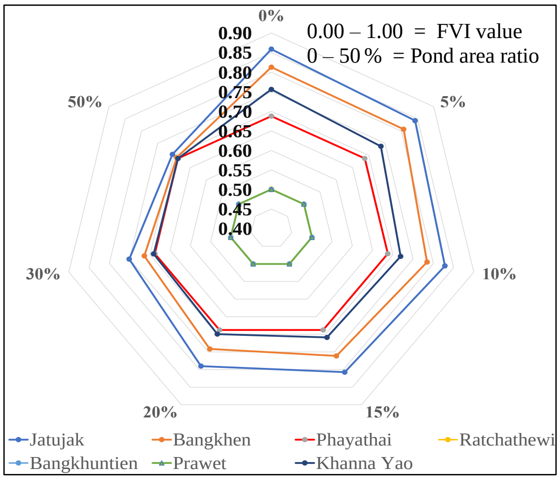


Figure 11 Relationship of FVI value with (%) Pond area Ratio

5. CONCLUSIONS

This study required a component of the resilience parameter to test for reducing the FVI value. Pond area ratio was used as a parameter in resilience to assess the storage area appropriately to reduce the sensitivity of the flood vulnerability index in each district.

The simulated results showed that after increasing parameter R, pond area ratio according to the feasible physical conditions of the areas with rainfall intensity of 76 mm/hr. It was found that the FVI of Chatuchak, Bangkhen, and KhannaYao districts could be reduced to 0.70 approximately. In contrast, the FVIs of the Phayathai and Ratchathewi districts could not be reduced due to the limited conditions of residential and business areas. Bangkhuntien and Prawet districts could not be reduced due to the Pond area ratio (PA) already having a high existing % PA and drainage system performance (DE) is 50%. Increasing % PA does not decrease FVI, Increasing % DE along may result in FVI values decrease. Therefore, these two districts should consider other measures such as warning systems or groundwater storage under a resilience perspective**.** The results of the studies mentioned above reveal that by reducing the FVI value in each region under different constraints, different local management methods or measures are required to integrate the appropriate system-wide management efficiency.

The flood vulnerability Index still depends on some assumptions. In addition to managing measures, it also requires people to be aware of disasters to cope and adapt to the conditions that occur. Therefore, the importance of disaster management has emphasized the ability of communities to respond to disasters, which is the most crucial factor in their work on preparedness and recovery. Because in fact, the first people to deal with disasters are the people and agencies in the disaster area.

The flood resilience concept brings to urban systems living with floods. The imperative is to acknowledge the importance of social, physical, and economic components when managing flood risk. The Flood Vulnerability Index (FVI) represents a tool for stakeholders and decision-makers. Different weights for evaluation FVI on a macro scale highlight the most important variables contributing to a higher level of resilience.

6. ACKNOWLEDGMENTS

The authors would like to thank the BMA GIS Center, Department of Drainage and Sewerage that provided data and would like to thank the Department of Water Resources Engineering, Kasetsart University, Bangkhen, Thailand.

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POTENTIAL OF HARVESTED RAINWATER FOR HOUSEHOLD CONSUMPTION: A CASE STUDY FOR RURAL DEMONSTRATION SITES IN THE NORTH-EAST OF THAILAND

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Abstract

During past several decades, Thai people in rural areas had used rainwater as drinking water in their households. However, the consuming of rainwater nowadays is not a normal practice anymore, people changed to bottled water owning to aware of rainwater contaminated by air pollution. Bottled water is not only costly, but also the bottles are hardly decomposed, deteriorate environment, and cause global warming and climate change phenomenon. The results of this study reveal that in selected study areas, Nong Khai and Ubon Ratchathani provinces, qualities of rainwater both in chemical and physical pass the Drinking Water Standard issued by Department of Health B.E. 2553, and annual rainfall volume in rainy season is plentiful. For that reason, rainwater in rural areas in Nong Khai and Ubon Rachathani can be considered as an alternative source of drinking water in households and as an adaptation measure for climate change during a long drought period.

In this study, 42 rainwater samples were collected from water storage containers (Ongs) in Nong Khai and Ubon Ratchathani during the late of rainy season in year 2019. Thereafter, the samples were transported to Bureau of Research Development and Hydrology, the Department of Water Resources to analyse their qualities. The future rainfall densities due to climate change are attained from predicted rainfall data from CMIP6 global circulation with MRI-ESM2-0 for both SSP245 and SSP585 future index analysis, performed by Hydro-Informatics Institute. The observed rainfall data from 1970 to 2020 by the Thailand Meteorological Department are used to validate results from CMIP 6. Consequently, the future rainfall volume in the Northeast of Thailand can be achieved with interpolation method by Arc Gis 10.5. With rainwater quality and rainfall quantity data, potential of rainwater harvesting to be an alternative source of drinking water for household consumption can be assessed.

Keywords: Potential rainwater, Drinking water, Harvesting, Observed rainfall, Modelled rainfall, Interpolation and Arc GIS 10.5

1. Introduction

The Northeast of Thailand (Isan) is located on the Khorat Plateau and covers 168,854 km^2 or one-third of the country. Isan had total population of 21,848,228 (NSO, 2020) [4]. It has three seasons, the summer season, the rainy season and the winter season. In general, the summer season is during middle of February and the middle of May, lasting for 3 months. The rainy season usually starts around middle of May and ends in the middle of October, approximately 5 months. Lastly, the winter season is about 4 months from mid-October to mid-February (TMD, 2020) [5].

In recent years, the Northeast of Thailand has been affected by climate change phenomenon. A long drought period in the summer deteriorated water sources both their quantity and quality. Without sufficient surface water or groundwater, water scarcities especially of potable water normally took place.

Rainwater is substantial abundance in Isan. With annual rainfall of 1,355 mm (TMD, 2020) [5], the amount of rainwater is sufficient to be harvested and spared as a source of drinking water. By comparison with surface water or groundwater, rainwater has its better quality. However, rainwater harvesting is out of favor nowadays, since ease of accessibility and availability of piped water supply and bottled water. Despite the fact that bottled water is not only considerable costly related to people's income, but also unhygienic in some cases. Therefore, if people return to gathering and sparing rainwater in the rainy season, it will increase their water security particularly of drinking water in their households throughout a dry period.

These days, Thai people do not drink rainwater any longer even in rural areas, owing to their concerns of contamination in rainwater caused by pollution. Only few of them have harvested and spared rainwater for general usage in their houses, and less of them have reserved it for consumption. As a result, without any source of clean water in the communities, villagers must pay for costly bottled water for their survivals.

In Thailand, rain harvesting scheme in the households commonly comprises with three components; roof (collection area), gutters and downpipes (delivery system), and water tanks (storage system). In this study, 42 samples were collected from water tanks in different households. Thereafter, they were kept in a temperature storage box at 3-5 ^{o}C and delivered within 24 hours to a laboratory at the Bureau of Research Development and Hydrology, Department of Water Resources to examine their qualities. The results from laboratory are compared with the Standard of Drinking Water issued by Department of Health B.E. 2553 to verify whether rainwater is safe for consumption.

Rainfall volume in the study areas is achieved by using monthly rainfall patterns under climate change phenomenon verified with observed rainfall data during 1980 to 2020. The future monthly rainfall patterns obtained from the CMIP6 global circulation by model named MRI-ESM2.0 and under SSP245 and SSP585 future scenarios (HII, 2021) [3]. The SSP245 is the medium part of the range of future forcing pathways, while SSP585 is the high end of the range of future pathways. Arc GIS 10.5 is executed to interpolate rainfall volume in Nong Khai, because no modelled rain station was set up in the province.

As a final step, rainfall patterns during the year 2020 and 2040 under climate simulation scenarios SSP245 and SSP585 are plotted in maps to achieve the monthly rainfall volume in Nong Khai and Ubon Rachathani. With the acknowledged data of rainwater qualities and rainfall quantities, the potential of rainwater harvesting to be potable water in household can be assessed.

2. Study sites

To assess a potential of rainwater harvesting for drinking purpose in Isan, Nongkhai and Ubon Ratchathani provinces were selected to be study areas.

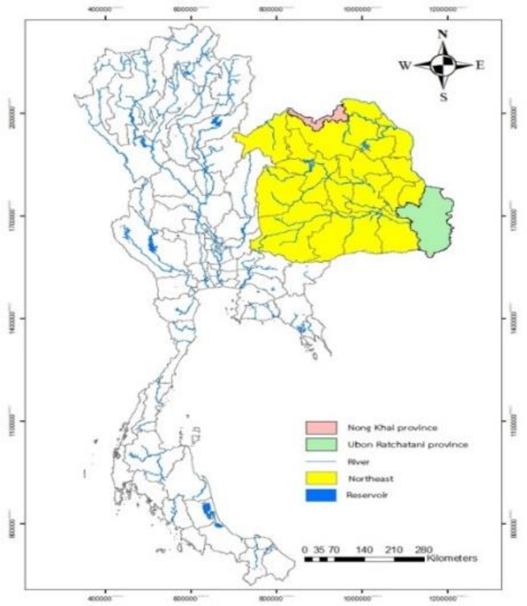

Figure 1a Location of Nongkhai and Ubon Ratchathani (DWR, 2018) [1]

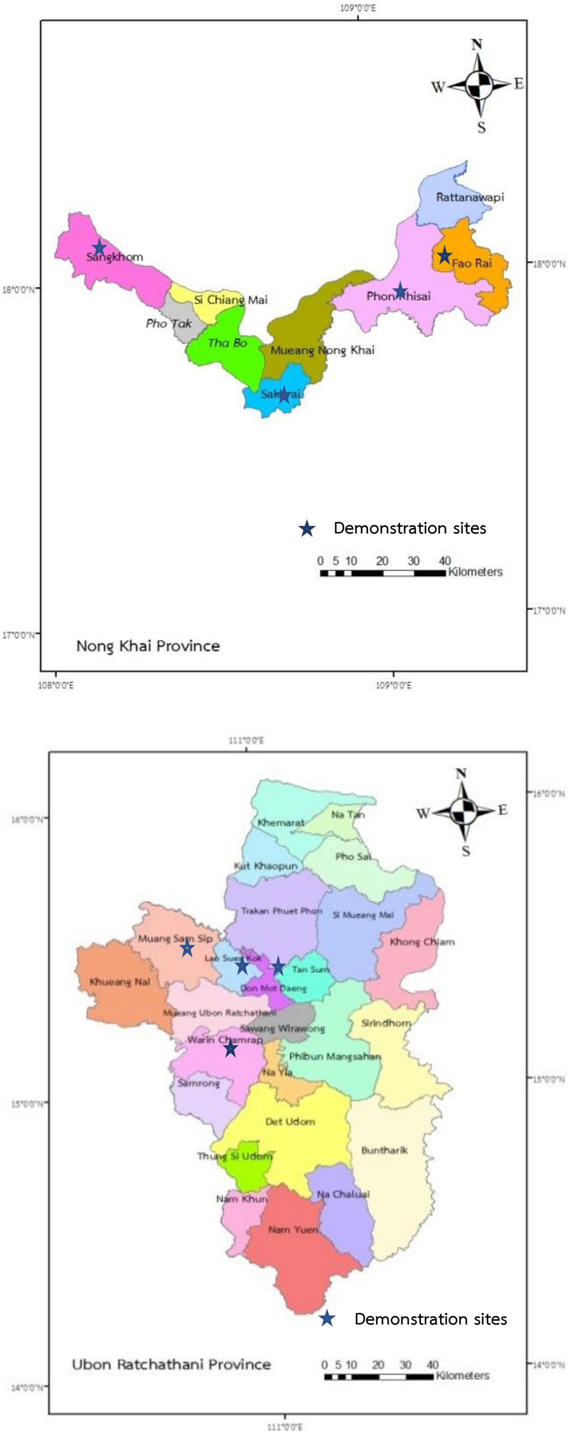

Figure 1 b Studied sites in Nongkhai and Ubon Ratchathani (DWR, 2018) [1]

It can be seen in Figure 1 a, it is not only that both cities are not densely with industrial activities, but also they are located far apart. Therefore, the studied rainwater quality parameters in 2 provinces are visibly dependent. Moreover, rainwater samples were collected in the different areas located far from the cities and considerable closed to agricultural areas, Figure 1b shows all studied sites where 42 rainwater samples were collected.

3. Potential of rainwater harvesting for household consumption

Nongkhai and Ubon Ratchathani were chosen to be studied areas in the beginning; however, the field investigation and sampling program were undertaken later in the late rainy season by means of traditional practice to obtain a good rainwater quality. All rainwater samples were collected from water storage vessels, at different houses dispersed cover the provinces. It could be observed from the site visit that most of rainwater harvesting systems were being neglected. Rusted galvanized corrugated iron sheets and over-hanging shrubs on roofs were noticed. Screen devices used to filter rain runoff in the conveyance system were hardly witnessed. The rainwater tanks were abandoned, with no periodically cleaning scheme. It could be understandable that stored rainwater is not well care-taken, since most people possibly reserve it for cleaning, washing, watering trees or other domestic purposes.

3.1 Rainwater Quality Analysis

A total number of 42 rainwater samples were collected during October 7-11, 2019. The 18 samples were collected in Nong Khai, while other 24 samples were collected in Ubon Ratchathani. Afterward, the samplers were taken to a laboratory at Department of Water Resources to analyze rainwater qualities. Subsequently, results of the analysis were verified with the Drinking Water Standard to confirm that rainwater is harmless for consumptions.

Demonstration sites	Contaminated parameters	Number of samples contaminated
Nong Khai Province (18 Samples)	Chemical	•1, Fluoride •1, Iron
	Physical	None
	Biological	•7 ,Total Coliform Bacteria andFecalColiform Bacteria •3, Total Coliform Bacteria
Ubon Ratchathani Province (24 Samples)	Chemical	None
	Physical	•3, Turbidity and Color
	Biological	•10,Total Coliform Bacteria and Fecal Coliform Bacteria •3,Total Coliform Bacteria

Table 1 The results of rainwater quality analysis

3.1.1 Results of rainwater quality analysis, Nong Khai province:

Eighteen rainwater samples were collected in different houses in 4 districts called Srakai, Phonepisai, Faorai and Sangkhom. The results from rainwater quality analysis show that 16 out of 18 rainwater samples (89%) pass the Drinking Water Standard in both physical and chemical parameters. Among 18 samples, 2 samples (11%) have chemical content, exceeding the standard, 1 sample in iron, another in fluoride. There are only 8 samples (44%) meeting the requirements of the biological standards. From total of 18 samples, 3 samples (17%) have total coliform bacteria values surpassing the standard, whereas 7 samples (39%) have total coliform bacteria and fecal coliform bacteria values exceeding the restriction, as depicted in Figure 2.

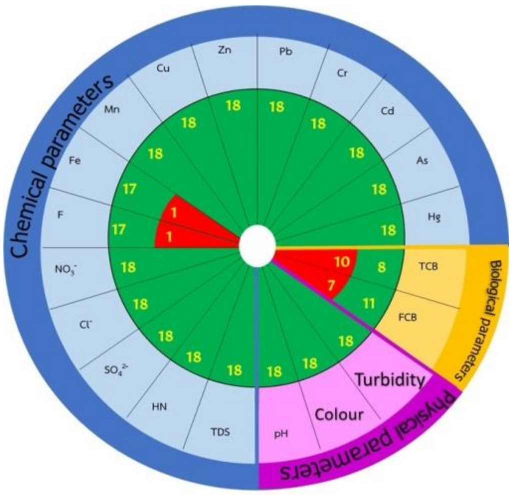

Figure 2 Results from rainwater analysis, 18 samples from Nong Khai

3.1.2 Results of rainwater quality analysis, Ubon Ratchathani:

Total number of 24 rainwater samples were collected from four districts; namely, Warinchamrab, Laosuekok, Donmoddaeng and Muangsamsib. The results show that 100% of rainwater samples have their properties passing the chemical standard. Regarding the physical standard, 21 samples (87%) were qualified, only 3 samples (13%) had turbidity and color values higher than the allowable limit. On the other hand, most of the samples (79%) failed to pass the acceptable biological values. There are 4 samples (17%) having total coliform bacteria value more than the standard, and 15 samples (62%) having total coliform and fecal coliform bacteria higher than the tolerable values as showed in Figure 3.

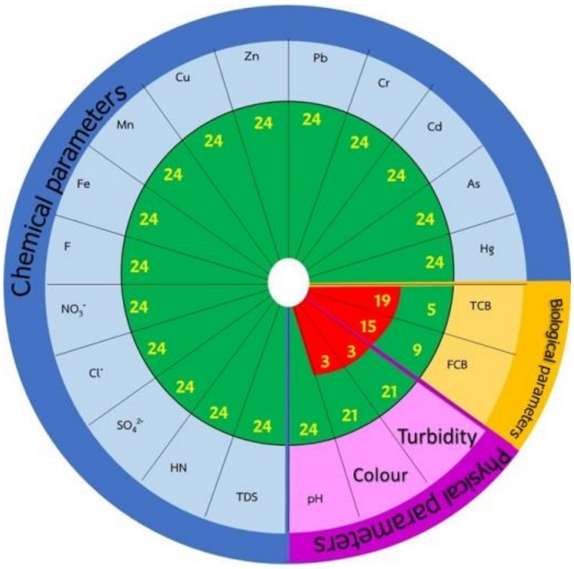

Figure 3 Results from rainwater analysis, 24 samples from Ubon Ratchathani

From the results of rainwater quality analysis, it is clear that rainwater samples from Nongkhai and Ubon Ratchathani have good qualities in physical and chemical aspects. Most of samples are not polluted with any hazardous substances nor heavy metals. In spite of that, most samples are unhygienic because of being contaminated by bacteria. This possibly caused by rain harvesting system is not well maintenance and rainwater is not stored and kept properly. However, this bacterial contamination problem can be managed straightforwardly by improving the rainwater harvesting system and sterilizing or disinfecting rainwater before consuming it.

3.2 Observed rainfall in Nong Khai and Ubon Ratchathani

The observed monthly rainfall data at 2 automatic rain gauges in Nong Khai and Ubon Ratchathani during 1970 and 2020 are showed in Figure 4.

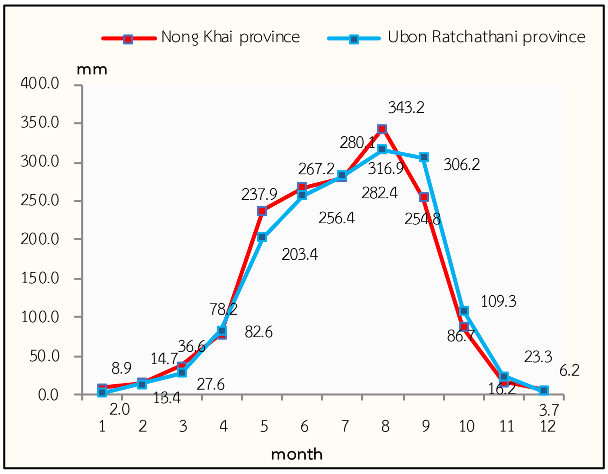

Figure 4 The observed monthly rainfall values in Nong Khai and Ubon Ratchathani during 1970 and 2020 (TMD, 2021) [2]

From Figure 4, the average monthly rainfall in the study sites in the rainy season during 1970 - 2020 are more than 200 mm. In Nong Khai province, the amount of rainfall is increasing from 237.9 mm in May to 343.2 mm in August and decreasing from 254.8 mm in September to 86.7 mm in October. Ubon Ratchathani province has similar monthly rainfall pattern. The rainfall volume is rising from 203.4 mm in May to the highest value of 316.9 mm in August and start falling from 306.2 mm in September to 109.3 mm in October. In dry seasons (summer and winter), the amount of rainfall value of both cities is less than 100 mm.

3.3 The observed and modelled monthly rainfall values in the Northeast

The average observed and modelled monthly rainfall values in the Northeast Thailand are plotted in Figure 5. The observed rainfall data from 14 rain stations and historical modelled rainfall data from 172 rain stations from 1980 to 2014 are calculated for finding the average values. It can be seen that shapes of two lines are similar. Both observed and modelled monthly rainfall values are increasing from January to May and continued rising until August or September. From October, both observed and modelled rainfall values start decreasing and finally become almost zero in December (Figure 5).

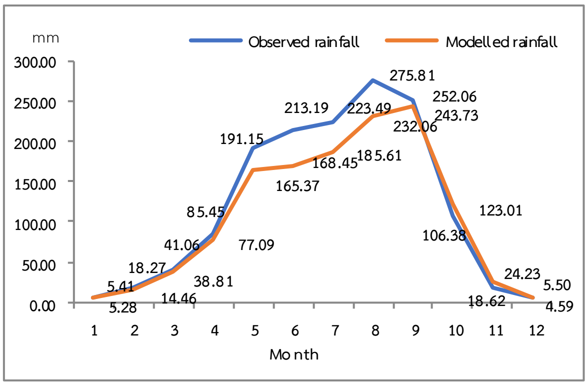

Figure 5 The comparison between observed and modelled monthly rainfall values in the Northeastern part of Thailand from 1980 to 2014 (TMD, 2021) (HII, 2021) [2,3]

Figure 5 shows that cumulative observed and modelled rainfall volumes in the rainy season during 1980 and 2014, are 1,262 mm and 1,118 mm, consecutively. The difference is only 11%, which can be acceptable.

3.4 The results of downscaled future climate of precipitation (future scenarios)

The modelled daily rainfall from 2020 to 2040 under SSP245 and SSP 585 simulation scenarios were performed by HII. Then, they are averaged for monthly and seasonal rainfall values, and presented in Figures 6 - 11.

3.4.1) The SSP 245 simulation scenario presents the medium part of the range of future forcing pathways and updates the RCP4.5 pathway (Reto, 2016) [6], the results of downscaled future climate of precipitation are presented in Figures 6-8.

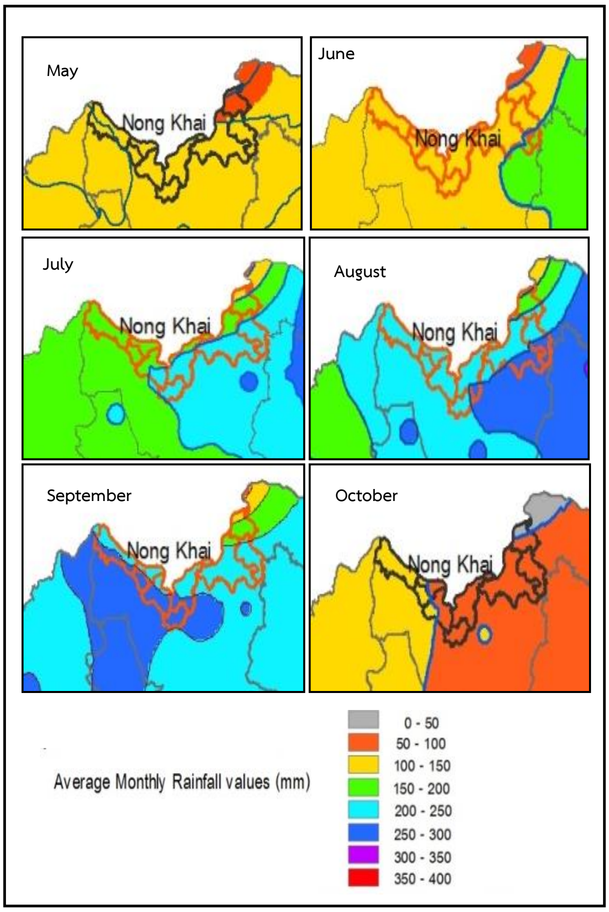

Figure 6 The average monthly rainfall values under scenario SSP 245 in rainy season from 2020 to 2040 in Nong Khai

Figure 6 and 7 present the monthly rainfall distributions in Nong Khai and Ubon Ratchathani. Nong Khai has the amount of rainfall approximately 100-300 mm during May to September, and 50-150 mm in October (Figure 6). Ubon Ratchathani has rainfall amount of 50-300 mm during May to September, and about 50-150 mm in October as depicted in Figure 7.

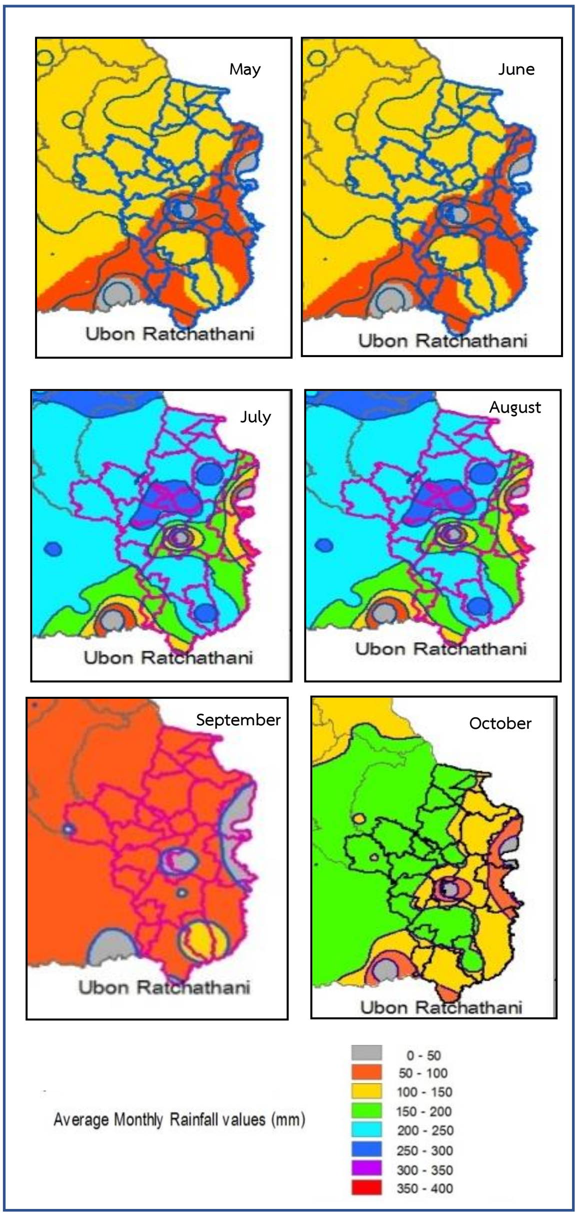

Figure 7 The average monthly rainfall values under scenario SSP 245 in rainy season from 2020 to 2040 in Ubon Ratchathani province

Figure 8 shows both provinces having the monthly rainfall volumes less than 60 mm in dry season.

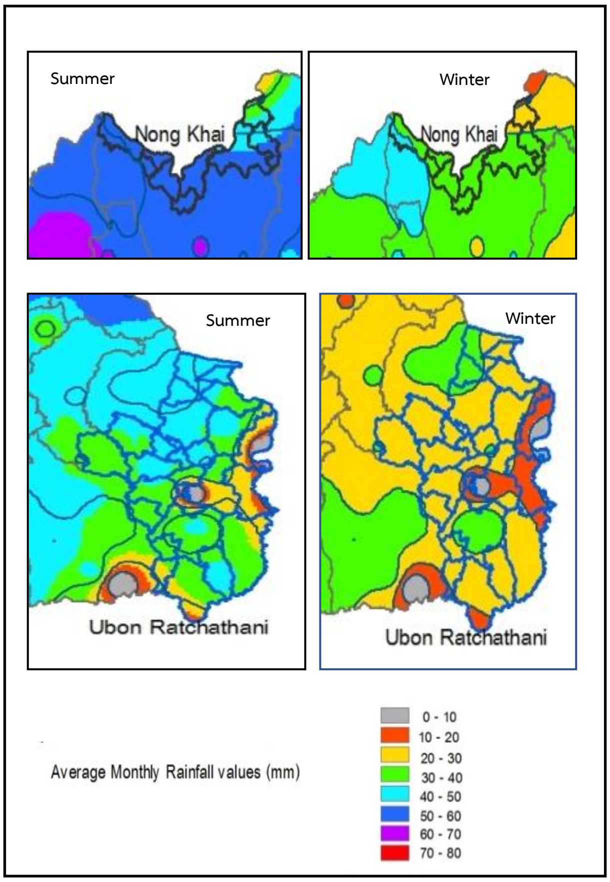

Figure 8 The average monthly rainfall values under scenario SSP 245 in dry season from 2020 to 2040 in Nong Khai and Ubon Ratchathani

3.4.2) The SSP 585 is the worst case scenario when the expansion of high emissions and coal use occur, without future climate policy. The average monthly and seasonal modelled rainfall values are showed in Figures 9-11.

Figure 9 shows spatial rainfall distributions, the average monthly rainfall values in Nong Khai from May to September are approximately 100-350 mm, and 100-200 mm in October. In Ubon Ratchathani, monthly rainfalls from May to September are between 50-350 mm, and it is less than 150 mm in October (Figure 10).

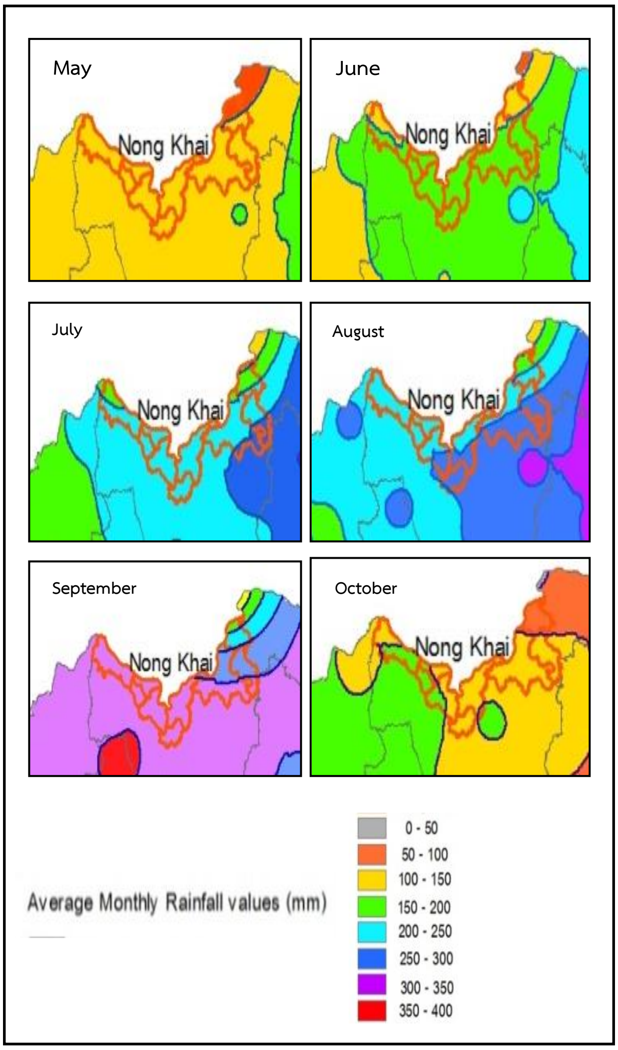

Figure 9 The average monthly rainfall values under scenario SSP 585 in rainy season from 2020 to 2040 in Nong Khai province

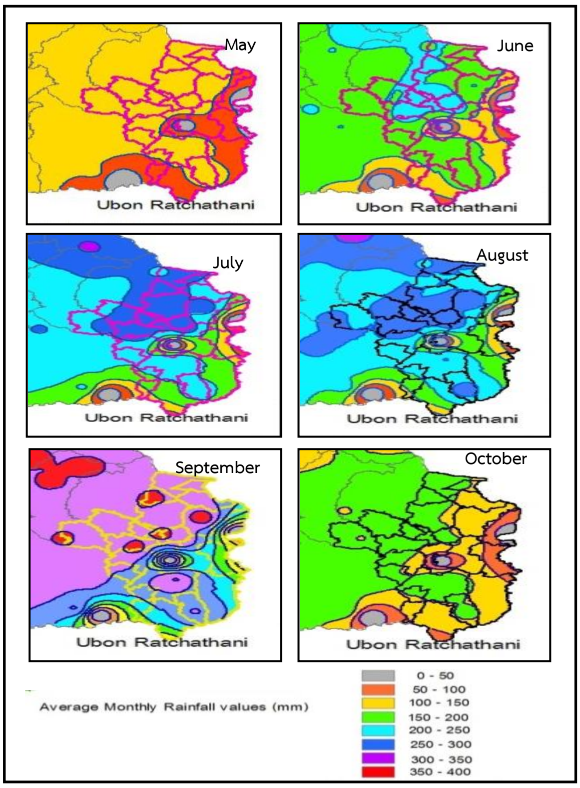

Figure 10 The average monthly rainfall values under scenario SSP 585 in rainy season from 2020 to 2040 in Ubon Ratchathani

Figure 11 shows that amount of rainfall values in both provinces are less 50 mm in the dry season.

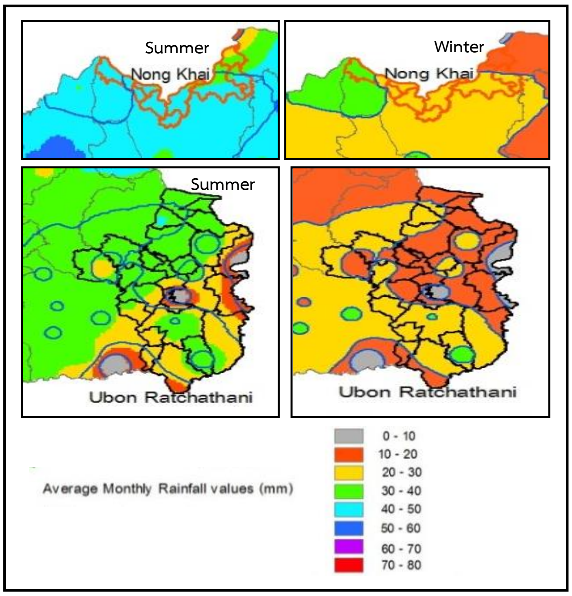

Figure 11 The average monthly rainfall values under scenario SSP 585 in dry season from 2020 to 2040 in Nong Khai and Ubon Ratchathani (HII, 2021)

3.4.3) The comparison of modelled rainfall values between SSP 245 and in SSP 585 simulation scenarios in Ubon Ratchathani.

It is seen in Figure 12 that tendencies of monthly rainfall in Ubon Ratchathani under SSP245 and SSP 585 scenarios are likely indifferent. They increase from May to September, and thereafter start decreasing. However, the SSP585 has heavier amount of rainfall than the SSP245 which are approximately 1,267 mm and 1,079 mm, consecutively.

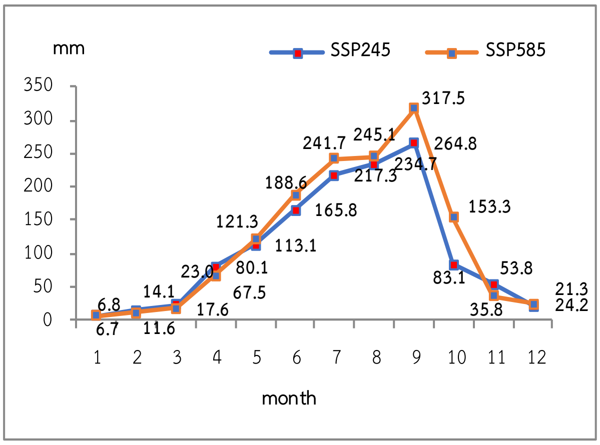

Figure12 Monthly rainfall values in Ubon Ratchathani from 2020 to 2040 under SSP245 and SSP585 (HII, 2021) [3]

3.5 Potential of rainwater harvesting for household consumption in the future

To study the potential of rainwater harvesting for household consumption, both quality and quantity of rainwater are taken into consideration. However, for the reason that rainfall patterns in Nong Khai and Ubon Ratchathani are similar, only an analysis of the potential in Ubon Ratchathani will be illustrated.

The laboratory results reveal that rainwater has its potential to be a safe source of drinking water, since its contamination is insignificant. Boiling can be a simple hygienic practice to achieve the disinfection. Therefore, another factor, the amount of harvested and stored rainwater, should be taken for further consideration.

Estimation of the amount of harvested rainwater in Ubon Ratchathani can be calculated as follows;

Annual yield (m^3) = ***Accumulative annual rainfall values in rainy season (mm) x Roof Area (m^2)***

Accumulative annual rainfall values in rainy season (mm) in the future from SPP245 and SSP 585 is equal to 1,079 mm and 1,268 mm.
Roof Area (m^2) is varied for each household *(circa 40 m^2, but used only ¼ of it for rainwater harvesting).* Therefore;

The annual yield of rainwater can be harvested is equal to 10.79 m^3 under SSP 245, and 12.48 m^3 under SSP585.

The required total volume of potable water throughout dry periods can be obtained from;

Required potable water (m^3) = Consumption per capita (cm^3) x No. of persons in household x drought duration (days) x 10^{-6}

Consumption per capita = 2,000 cm^3 (drinking water/person/day)

No. of persons in household = 4

Drought duration = 210 days

Therefore, the required volume of drinking water for the household consumption is equal to

= 2,000 x 4 x 210 x 10^{-6}

= 1.6 m^3 per household

It can be realized that the required volume of drinking water for each household consumption of 1.6 m^3 is much less than the annual yields of rainwater of 10.79 m^3 under SSP245 and of 12.48 m^3 under SSP585. Therefore, this study assures that an amount of annual rainfall is sufficient to be collected and reserved for consuming in the households.

4. Conclusion and Discussion

The Northeast Thailand has abundance amount of annual rainfall, especially in areas of demonstration sites. With a right number of storage tanks, the amount of rainfall is adequate to be harvested and stored for consumption for each family during the dry period. No heavy metal was detected in the rainwater samples. Bacterial contamination in water was slight and can be disinfected by boiling. With the above mentioned reasons, rainwater can be a water source for drinking, especially when other water sources are inaccessible or unavailable during a long dry season. Rainwater harvesting can be an adaptation measure to mitigate the impacts of climate change to ensure a sufficient supply of potable water in a household in the future.

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THE PREDICTABILITY OF RESERVOIR INFLOW PREDICTION MODEL FOR SIRIKIT DAM USING XGBOOST MACHINE LEARNING ALGORITHM

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ABSTRACT

XGBoost which is a tree–based ensemble machine learning algorithm, was used to predict the daily and monthly reservoir inflows of the Sirikit Dam, Thailand. Training and testing the prediction models were accordingly implemented using observed inflow and climate data during 2000–2020 as the key prediction inputs. The correlation analysis was conducted to seek the strong relations between the observed inflow of the Sirikit Dam and climate data collected from TMD and NASA data sources. Setting up the prediction model structures were performed using observed inflow, precipitation and humidity data at time step t, and the average inflow at the delayed time steps. Consequently, 54 scenarios of XGBoost daily and monthly models were trained and evaluated by altering the model parameters such as ratio of training–training datasets, learning rates, maximum number of iterations, and early stopping rounds. It is found from the validation results that the XGBoost model could present more reliable and robust prediction results especially for the daily prediction model with the highest R^2, R, NSE of 0.8362, 0.9145, and 0.8161, respectively. In addition, small values of RMSE and MSE were considerably found. The predictability of the XGBoost model to predict the daily reservoir inflow with good precision is strongly higher than the monthly inflow. Predicting the average values of the daily and monthly inflows gives the prediction results definitely closer to the observed inflows. However, the capability to characterize and predict the dynamics of extreme values of these two developed models is still weak. Therefore, to improve the quality of machine learning algorithm for hydrological prediction, the model parameters need to be optimized. Moreover, conducting the further study using the technological advancement of machine learning is highly encouraged for the achievement of hydrological forecast on water resources management.

Keywords: Artificial Intelligence (AI), Extreme Gradient Boosting (XGBoost), Machine Learning (ML), Reservoir Inflow Prediction, Sirikit Dam

1. INTRODUCTION

The natural disaster occurrences like floods and droughts have been frequently occurred in Thailand. These have become a serious and significant problems in water resources planning and management of the country. Due to the occurrences of major flood in 2011 and the severe drought in 2020, these flood and drought events created a huge agricultural and economic losses of the country particularly in the central and northern regions in the Greater Chao Phraya River Basin. The Greater Chao Phraya River Basin is considered as the largest basin having the irrigation service area of more than 8 million rai along the Chao Phraya, Lower Ping, and Lower Nan Rivers. The main storage dam; Sirikit Dam, was constructed across Nan Rivers in the Nan River Basins, where the headwater of the Chao Phraya River begins and flows into the Gulf of Thailand. The water supply sources in this basin primarily come from the Sirikit reservoirs with the total capacity of 9,510 million cubic meters. It is reported that the reservoir inflow of Sirikit Dam has become significantly decreased since flooding event occurred in 2011. The average inflows during 2012–2019 of the Sirikit Dam have been declined by approximately 10% of the average long–term record. Moreover, high spatial variability of hydrological changes in the basin such as rainfall and climate data has considerably influenced the volume of reservoir inflows of the dam.

Hydrological prediction remains the difficult and challenging tasks. However, the prediction of hydrological data plays significant role in multi–reservoir operation. It would be emphasized that the precision of rainfall and reservoir inflow forecasts are necessary in decision making process to determine the dam release. In general, the quality of hydrologic prediction is identified by the degree of prediction accuracy and prediction techniques applied. The Artificial Intelligence (AI) have acted as the main driver of emerging technologies for hydrologic forecast nowadays [1]. Cerqueira et al. [2] compared machine learning and statistical methods for time series forecasting. It shows that statistical methods are only valid under an extremely low sample size. The results also suggest that machine learning using a learning curve method can improve the predictive performances as the sample size gradually grows. The machine learning which is a branch of artificial intelligence has been widely applied in the field of water resources engineering with the great success for hydrological predictions. Mosavi et al. [3] presented the overview of machine learning techniques for flood prediction instead of using the physically–based and statistical models which were long used to predict hydrological events. In general, the prediction models can be divided into two categories according to prediction lead–time, and they can be categorized into hybrid and single methods. The ability to produce the accurate forecasts of hydrological data with long, medium, and short lead times using Artificial Intelligence with Machine Learning (ML) has been highly proven and exhibited through many research studies. Extreme Gradient Boosting (XGBoost) which is a novel machine learning algorithm, was initiated in 2014. It was developed from Gradient Boosting [4] as an ensemble learning method for classification and regression problems. Due to its excellent learning performance and effective training speed, considerable attention on XGBoost algorithm has been paid for hydrological prediction. It is revealed that XGBoost algorithm can be a powerful predictive tool creating more remarkable prediction accuracy and generalization ability than existing algorithms such as Support Vector Machines (SVM), Random Forest (RF) and K–Nearest Neighbor (K–NN) algorithm [5]. In addition, Ni et al. [6] developed a hybrid model using extreme gradient boosting algorithm coupled with Gaussian mixture model (GMM–XGBoost), for monthly streamflow forecasting and compared the results with SVM and standalone XGBoost. Although all three prediction models yielded quite good performance on one–month ahead forecasting, however, GMM–XGBoost provided the best accuracy with significant improvement of forecasting accuracy. Machine learning was also applied for the prediction of variations in groundwater levels in Malaysia [7]. The modelling exercises were conducted using XGBoost, Artificial Neural Network, and Support Vector Machines for ground water level prediction. It can be comparable among these selected algorithms that applying the XGBoost algorithm performed very well for all the input combinations. Moreover, it can be served as a great benchmark for future hydrological prediction.

Therefore, this study focuses on an evaluation of predictability of prediction models by machine learning for reservoir inflow prediction. The extreme gradient boosting algorithm (XGBoost) and R programming language were employed to develop the daily and monthly inflow prediction models of the Sirikit Dam, Thailand.

2. METHODOLOGY

2.1 Study Area and Data Selection

The Sirikit Dam is a largest earth–filled dam in Thailand built across Nan River in the Nan River Basin in the northern region of Thailand. Nan River Basin is considered as one of the eight sub–basins of the Greater Chao Phraya River Basin (GCPYRB) which originates water supply source for multiple water uses in the Lower Nan and Chao Phraya River Basins. The Sirikit Dam has the reservoir capacity of 9,510 MCM covering drainage area of 13,130 km^2. Due to the physical features of natural land area above the Sirikit Dam, high spatiotemporal variability on the precipitation has been found in this region. This has affected on the extent of reservoir inflow of the Sirikit Dam especially in rainy season between May to October. The basic statistics of climate data and reservoir inflow of the Sirikit Dam collected from 2000–2020 (21 years) are summarized in Table 1.

Table 1 Descriptive statistics of climate and reservoir inflow data in the study area

Required data	Values	Time of Occurrence
Max. daily prec.	145.60	04/09/2011
Max. monthly prec.	457.80	09/2011
Max. daily evap.	3.54	24/01/2014
Max. monthly evap.	37.72	04/2003
Peak daily inflow	221.87	12/08/2001
Peak monthly inflow	3,095.97	08/2011

Remark: Precipitation (Prec.) and evaporation (Evap.) data are presented in millimeter (mm) and reservoir inflow is displayed in million cubic meters (MCM)

The influence of climate data on the predictive performance of reservoir inflow prediction models was also illustrated in this study. Consequently, the type and amount of data inputs, and the correlation coefficient measuring the strength of relationship of two data were considered for data selection. It would say that the preparation and selection of data is definitely critical to the success of a machine learning solution. Therefore, selecting the data inputs to identify the model structures was based on the climate station sites nearby the Sirikit Dam and strong correlation between selected climate data and the reservoir inflow. Accordingly, the daily observed climate data such as precipitation, humidity, minimum and maximum temperature were collected during 2000–2020 from three climate stations of the Thai Meteorological Department (TMD) namely Station 0003, 0018, 0095 which are located in Phitsanulok, Uttaradit and Nan Provinces, respectively (in Fig.1). In addition, a large number of climate data at the same geographic coordinates of TMD climate stations placed in the vicinity of the reservoir site was also gathered from the Climate Data Services (CDS) publicly provided by the National Aeronautics and Space Administration (NASA). Moreover, the observed inflow considering as major data for the development of daily and monthly prediction models was provided by the Electricity Generating Authority of Thailand (EGAT).

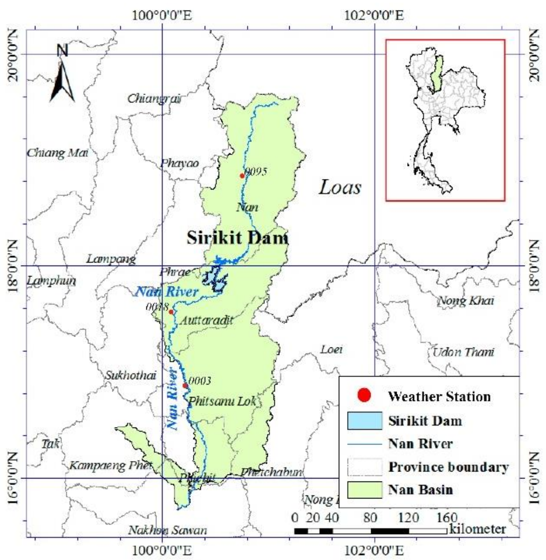

Figure 1 Study area and climate stations used in this study

The correlation analysis gave the strong relations between the observed inflow of the Sirikit Dam and precipitation and humidity data collected from TMD and NASA sources as summarized in Table 2. These data were selected to identify the prediction structures of daily and monthly models by machine learning in this study.

Table 2 The correlation coefficients between the observed reservoir inflow and climate data

Station	Data	Corr.	Data Sources
SK Dam	Obs. Inflow	1.0000	EGAT
0003 Phitsanulok N 16°47’47.0’’ E 100°16’32.9”	Prec.	0.0382	TMD
	Prec.	0.3761	NASA
	Hum.	0.4282	TMD
	Hum.	0.5356	NASA
0018 Uttaradit N 17°37’00.0’’ E 100°05’60.0”	Prec.	0.1673	TMD
	Prec.	0.4056	NASA
	Hum.	0.4991	TMD
	Hum.	0.5034	NASA
0095 Nan N 18°46’01.0’’ E 100°45’47.2”	Prec.	0.0024	TMD
	Prec.	0.3923	NASA
	Hum.	0.5348	TMD
	Hum.	0.4689	NASA

2.2 Extreme Gradient Boosting (XGBoost) Algorithm for Reservoir Inflow Prediction

To develop the daily and monthly prediction models of reservoir inflow of the Sirikit Dam, the Extreme Gradient Boosting (XGBoost) which is a decision–tree–based ensemble machine learning algorithm, was used in this study.

XGBoost is broadly utilized for supervised learning problems, where the training data y_i is used to predict a target variable p_i. The following shows the basic elements of supervised XGBoost learning that relies on minimizing the objective function. The group of functions that are minimized are called “loss functions”. p_i is expressed as a variety of tasks such as regression, classification, and ranking. The task of training the model is to find the best parameters θ that best fit the training data y_i and label p_i. To train the model, the objective function measuring how well the model is suited with the training data, should be defined. In general, a characteristic of objective functions contains two main terms; (1) training loss function and (2) regularization term as expressed in Eq. (1)

$$Obj(\theta) = L(\theta) + \Omega(\theta) \quad (1)$$

where, θ represents the best parameter that fits the training inflow data (y_i) and predicted output (p_i). $L(\theta)$ is the training loss function which can be categorized into two types; classification and regression losses. A common type of regression loss is mean squared error as given in Eq. (2).

$$L(\theta) = \frac{1}{2}\sum_{i=1}^{n}(y_i - p_i)^2 \quad (2)$$

The regularization term $\Omega(\theta)$ in Eq. (3) is one of the significant term that helps control the complexity of the model and avoid overfitting.

$$\Omega(\theta) = \gamma T + \frac{1}{2}\lambda \sum_{i=1}^{T} O_{value}^2 \qquad (3)$$

where, γ is hyperparameter that is used to define the minimum loss reduction required to make a further partition on a leaf node of the tree. T is the number of terminal nodes or leaves of a tree. λ is a parameter used to handle the regularization part of XGBoost. O_{value} is an output value for the leaves to minimize the whole equation.

The prediction for one given data is made by following the tree until the final node for prediction is accomplished. The tree is built from single leaf or root node. After that, the root node is split the leaf on the left and the leaf on the right. It keeps building trees until the errors are super small. Fig.2 illustrates the decision tree components of XGBoost.

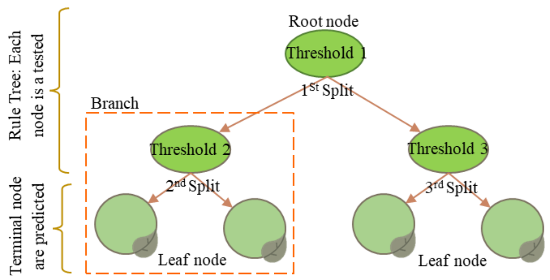

Figure 2 The decision tree components of the XGboost

The loss function $L(\theta)$ indicates the scores of the tree and leaf. It is noticeable that learning the tree structure is much more difficult than traditional optimization problems. It is intractable to learn all the trees at once. Instead, we use an additive strategy: fix what we have learned and add one new tree at a time. Similarity score is computed (Sim) to indicate a score of each node by using Eq. (4).

$$Sim = \frac{\sum_{i=1}^{n} (y_i - p_i)^2}{n + \lambda} \qquad (4)$$

After that, the Gain value is calculated to measure how good a tree structure is. The Gain value indicates whether a tree can split the leaves or not. When the gain values are negative, the branch is removed as shown in Fig.3. This is actually called as the pruning techniques in tree–based models.

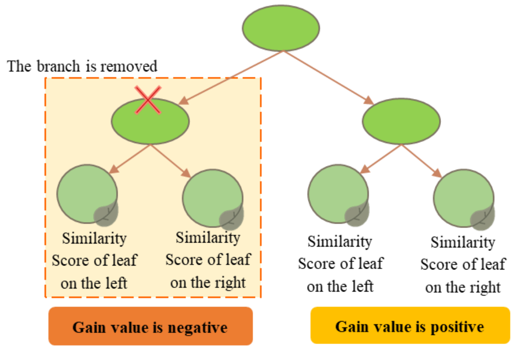

Figure 3 Steps to split the decision tree using Gain value

Ideally, we would enumerate all possible trees and pick the best one. The Gains values are illustrated in Eq. (5).

$$Gain\ value = Sim_{left} + Sim_{right} + Sim_{root} \qquad (5)$$

where, Sim_{left}, Sim_{right}, and Sim_{root} represent the similarity score of the leaf on the left side, the right side, and the root node of the branch, respectively.

The tree structures are iterated for T iterations until the required number of models are built. Building the iterative tree are finally stopped. The output values (O_{value}) are calculated by Eq. (6) for all leaves to get the final tree at the end of first model since some leaf has more than one residual.

$$O_{value} = \frac{\sum_{i=1}^{n} (y_i - p_i)}{n + \lambda} \qquad (6)$$

In addition, the precision of prediction model is controlled by learning rate (eta: ε). The learning rate must be set appropriately to obtain accurate prediction results and avoid overfitting.

In this study, the prediction of reservoir inflow at time t (p_i^t) by XGBoost is the additive sum of all previous predictions made by the model. In other words, the final prediction is the additive sum of the initial predicted value (p_i^0) and objective function combining with loss function and a regularization term, as shown in Eq. (7).

$$p_i^t = p_i^0 + \varepsilon\left[\sum_{i=1}^{n} L\left(y_i, p_i^0 + O_{value}\right) + \frac{1}{2}\lambda O_{value}^2\right] \qquad (7)$$

2.3 Evaluation of Prediction Model Performance

To evaluate the prediction model performance, the statistical methods; Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Coefficient of Determination (R^2), Coefficient of Correlation (R), and Nash–Sutcliffe Efficiency (NSE) were used to indicate the perfect match between the predicted values and observation values. The RMSE and MSE are frequently used to evaluate how closely the prediction result match the observation data based on standard deviations [8]. The R and R^2 are statistical measures describing the degree of linear correlation between two independent variables [9]. The NSE is the normalized statistic that determines the relative magnitude of the residual variance compared to observed data variance [10].

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - p_i)^2}{n}} \quad (8)$$

$$MSE = \frac{\sum_{i=1}^{n}(O_i - p_i)^2}{n} \quad (9)$$

$$R^2 = \left[\frac{\left(\sum_{i=1}^{n}(O_i - \bar{O})\cdot(p_i - \bar{p})\right)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2 \cdot \sum_{i=1}^{n}(p_i - \bar{p})^2}\right] \quad (10)$$

$$R = \frac{\sum_{i=1}^{n}(O_i - \bar{O})\cdot(p_i - \bar{p})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2 \cdot \sum_{i=1}^{n}(p_i - \bar{p})^2}} \quad (11)$$

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(O_i - p_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}\right] \quad (12)$$

In the Eq. (8) – (12), O_i and p_i are observed inflow and predicted inflow at time t, respectively; $\bar{O}$ and $\bar{p}$ are the average values of observed inflow and predicted inflow, respectively, and n is the number of observations.

The R and R^2 values range from –1 to 1 and 0–1, respectively. It implies a perfect fit when RMSE and MSE values are approach to 0. The NSE value ranges between –∞ to 1. The XGBoost model produces reliable and robust prediction results when the R and R^2 are relatively approach to 1, RMSE and MSE values are small, and NSE value should be approximately 1.

2.4 Development of Reservoir Inflow Prediction Models

RStudio; an open–source software library for R programming, was used in this study to develop the reservoir inflow prediction model of the Sirikit Dam through machine learning. As aforementioned in *2.1*, selecting the input variables for the development of prediction models was carried out through the analysis of correlation to ensure that the prediction model can capture the strong relationship between the inputs and target variable (reservoir inflow). Therefore, setting the model structures were performed corresponding to the model input variables selected, the ratio of training–testing dataset (60:40/70:30/80:20), number of average inflow at the delayed time steps (3 and 7), climate and observed inflow data at time step t, and learning rates (0.1/0.01/0.001). The prediction model inputs were observed inflow at time step t, average inflow at the delayed time steps t–1,…., t–3, average inflow at the delayed time steps t–1,...., t–7, precipitation at time step t, and humidity at time step t. Consequently, 54 scenarios of XGBoost daily and monthly models (@3×2×3×3) were trained and evaluated to produce good prediction results as shown in Fig.4.

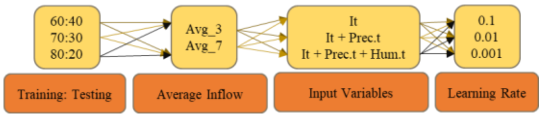

Figure 4 Input variables and model parameters for developing the reservoir inflow prediction models

A number of training options and several model parameters were tested to find the best predictive performance of the reservoir inflow. The adaptive parameters of the XGBoost were also updated depending on given loss function of an iteration step. The workflow of model development for reservoir inflow prediction by XGBoost algorithm is illustrated in Fig.5

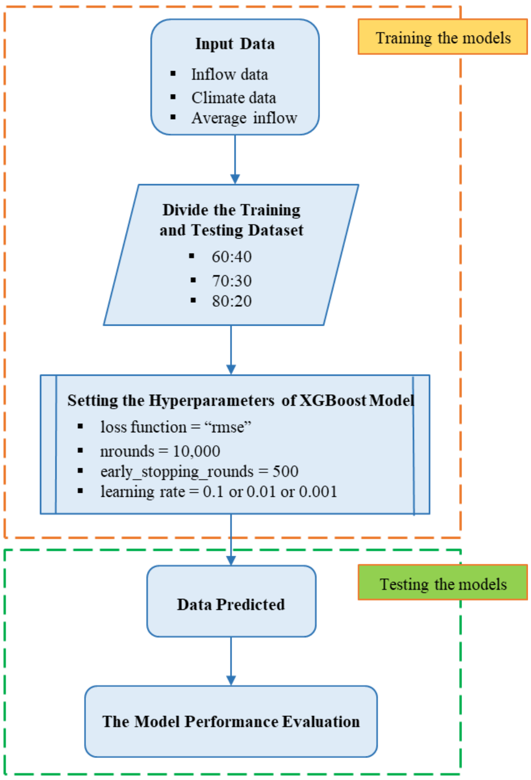

Figure 5 The workflow of model development for reservoir inflow prediction

Firstly, input data was imported into the model. Secondly, the time series of selected inputs were divided into training and testing datasets according to the designated ratio. Thirdly, implementation of XGBoost training model was controlled by the hyperparameter setting [11, 12] such as number of iterations (*nrounds*), learning rate (*Eta*), and early stopping rounds (*early_stopping_rounds*) parameters. Accordingly, the maximum number of iterations was 10,000. The learning rate allows model to achieve faster convergence of training dataset. So, the learning rates of 0.1, 0.01, and 0.001 were determined in this study. The early stopping rounds are generally used to stop training procedures when the loss on training dataset starts increasing. In this study, the early stopping round was set every 500 iterations if the performance on RMSE was not improved.

3. RESULTS AND DISCUSSIONS

3.1 The Predictive Performances of the Reservoir Inflow Prediction Models of Sirikit Dam

The predictive performances of two prediction models of Sirikit Dam; daily and monthly models; were considerably evaluated in terms of quantitative and qualitative manners as summarized in Table 3. Moreover, the qualitative comparison between observed and predicted inflows of the best daily and monthly prediction models were also investigated in Table 4 to reassure that the prediction model could yield good predictive results representing the occurrences of climate–related extreme events.

The result of correlation analysis in Table 2 shows that the precipitation data collected from observed station of TMD and NASA data services at Station 0018–Uttaradit gave higher correlation with the reservoir inflow with 0.1673 and 0.4056, respectively by comparing with other neighboring climate stations nearby the Sirikit Dam. Therefore, two important variables of climate data; precipitation and humidity of Station 0018 were then considered to identify the model structures for prediction. In addition, the moving average of reservoir inflow at the delayed time steps and observed inflow at time step t were also used as key inputs in the prediction models.

It was appeared when 54 scenarios of daily prediction models were validated that the input structure of the best daily prediction model was the observed inflow at time step t, and average inflow at the delayed time steps t–1,…., t–3. For 54 scenarios of the monthly models, the best input structure for prediction was the observed inflow at time step t, average inflow at the delayed time steps t–1,…., t–7, and precipitation at time step t at Station 0018. The predictive performance for the daily model after the validation process reached high up to 0.8362 of R^2 and 0.8161 of NSE. However, it is found that the predictive performance became lower for the monthly model with 0.5196 of R^2 and 0.5128 of NSE.

Moreover, separating the training and testing datasets using 80:20 and 70:30 ratio gave the robust performance for the daily model and monthly model, respectively. The effect of moving average of reservoir inflow identified as the prediction inputs (avg_3, avg_7) did not alter much on the predictive performances of daily and monthly models.

The important role of learning rates on the predictive performance is also exhibited in Fig.6. It is illustrated that when the learning rates of 0.1, 0.01, and 0.001 were identified, the root mean square of prediction errors were profoundly decreased within the number of iterations of 10,000 for both the training dataset (green line) and testing dataset (red line). However, suitable learning rates were 0.1 for the daily prediction model and 0.001 for the monthly prediction model.

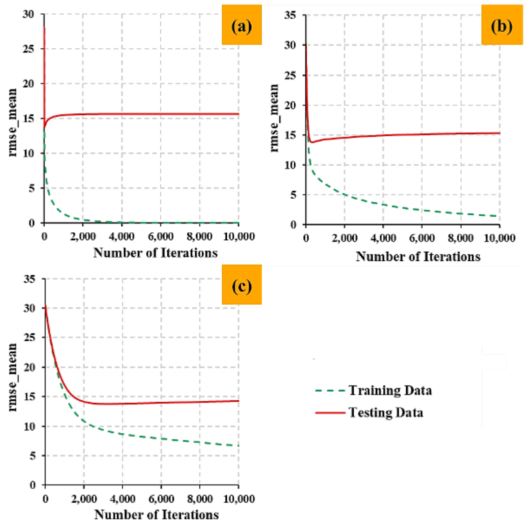

Figure 6 The relationship between number of iterations and root mean square of prediction errors (rmse_mean) for the learning rate of (a) 0.1, (b) 0.01, and (c) 0.001

3.2 Comparison of Predicted Inflows Obtained from the Best Daily and Monthly Prediction Models and Observed Inflows of Sirikit Dam

The quantitative and qualitative comparison between observed and predicted inflows of the best daily and monthly models are presented in Table 4 and Fig.7–8. It can be seen in Fig.7 that the daily predicted inflows were definitely closed to the daily observed inflows for both the training and testing datasets when daily prediction model was performed. In addition, the average daily inflow performed by the daily prediction model was really closed to the observed values with small percentage difference of -3.58% and -2.38% for the training and testing datasets, respectively as shown in Table 4.

The volume error of average daily inflow were -0.62 and -0.34 MCM for the training and testing datasets, respectively which were slightly underestimated. However, it showed higher percentage of underestimation of -33.77% (-74.92 MCM) and -46.78% (-102.31 MCM) for the training and testing datasets when comparing the daily peak flows made by the daily prediction model with the observed values. This reflected that daily prediction model could not implement well to predict the extreme events.

Fig.8 depicts the qualitative performance of the best monthly prediction model for reservoir inflow of Sirikit Dam. It was likely similar in term of the inflow pattern between the observed and predicted inflows during 2000–2020. However, higher percentage difference was found for the monthly prediction models when the average and peak inflows were considerably investigated as shown in Table 4. The volume error of average monthly inflow were -46.96 and +1.74 MCM for the training and testing datasets, respectively. The percentage difference of the average monthly inflow was -8.91% for the training dataset and +0.39% for the testing dataset. It showed higher percentage of underestimation of -32.98% (-1,021 MCM) and -27.16% (550 MCM) for training and testing datasets when comparing the monthly peak flows with the observed values.

This signifies that predictive performance of daily prediction model is more reliable and robust than the monthly prediction model. Moreover, the capability to characterize and predict the dynamics of extreme values is still weak.

Table 3 The predictive performance of the reservoir inflow prediction models of Sirikit Dam during 2000–2020

Model setting	Model Inputs	Daily prediction model			Monthly prediction model		
Training: Testing Ratio	–	60:40	70:30	80:20	60:40	70:30	80:20
Inputs	Avg. Inflow t–1 to t–3 (Avg_3)	✓	✓	✓	–	–	–
	Avg. Inflow t–1 to t–7 (Avg.7)	–	–	–	✓	✓	✓
	Inflow t (It)	✓	✓	✓	✓	✓	✓
	Prec.t	–	–	–	✓	✓	✓
Learning rate	–	0.1	0.1	0.1	0.01	0.001	0.01
Training dataset	RMSE	8.7749	8.6989	8.3666	485.0587	443.3527	428.8864
	MSE	76.9993	75.6713	69.9998	235,281.95	196,561.61	183,943.56
	R^2	0.8890	0.8843	0.8837	0.4643	0.4928	0.4984
	R	0.9428	0.9404	0.9400	0.6814	0.7020	0.7059
	NSE	0.8740	0.8675	0.8711	0.4191	0.4727	0.4803
Testing dataset	RMSE	8.4261	8.7146	9.0171	363.4004	358.2783	376.2822
	MSE	70.9985	75.9451	81.3076	132,059.86	128,363.36	141,588.32
	R^2	0.8267	0.8310	0.8362	0.4847	0.5196	0.5090
	R	0.9092	0.9116	0.9145	0.6962	0.7208	0.7134
	NSE	0.8176	0.8124	0.8161	0.4424	0.5128	0.5054

Table 4 Comparison of predicted inflows obtained from the best daily and monthly prediction models and observed inflows of Sirikit Dam

Model type	Daily					
Model parameters	Training–Testing Ratio: 80:20					
	Inputs: Avg. Inflow t–1 to t–3					
	Learning Rate: 0.1					
Predictive performance	Average inflow (MCM/day)			Peak inflow (MCM/day)		
	Observed	Predicted	Δ (%)	Observed	Predicted	Δ (%)
Training data set	17.32	16.70	-0.62 (-3. 58)	221.87	146.95	-74.92 (-33.77)
Testing data set	14.26	13.92	-0.34 (-2.38)	218.70	116.39	-102.31 (-46.78)
Model type	Monthly					
Model parameters	Training–Testing Ratio: 70:30					
	Inputs: Inflow t, Avg. Inflow t–1 to t–7, Precipitation t					
	Learning Rate: 0.001					
Predictive performance	Average inflow (MCM/month)			Peak inflow (MCM/month)		
	Observed	Predicted	Δ (%)	Observed	Predicted	Δ (%)
Training data set	527.03	480.07	-46.96 (-8.91)	3,095.97	2,075.05	-1,020.9 (-32.98)
Testing data set	441.00	442.74	+1.74 (+0.39)	2,026.29	1,475.96	-550.33 (-27.16)

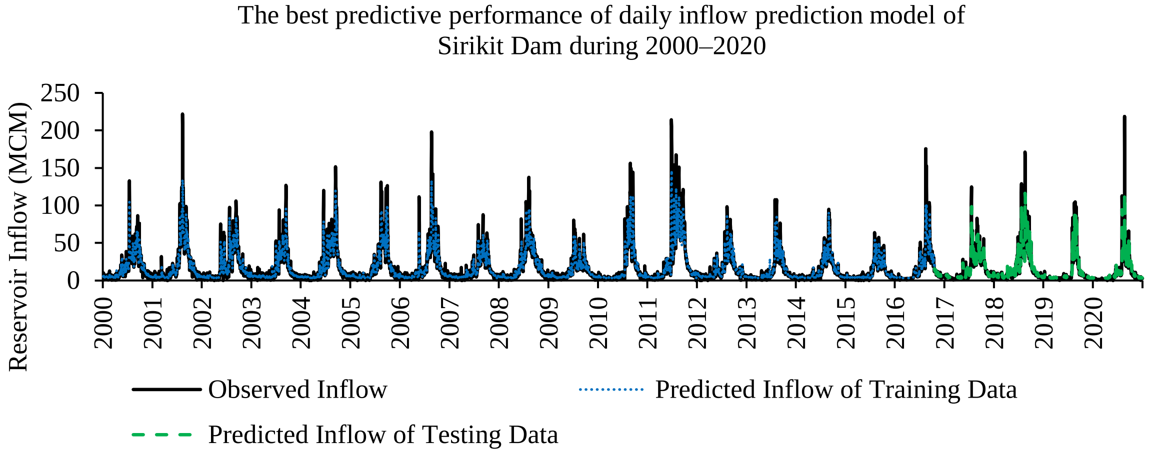

Figure 7 The qualitative comparison between observed and predicted inflows of the best daily model with model parameters: Training–Testing Ratio: 80:20, Inputs: Avg. Inflow t–1 to t–3, Learning Rate: 0.1

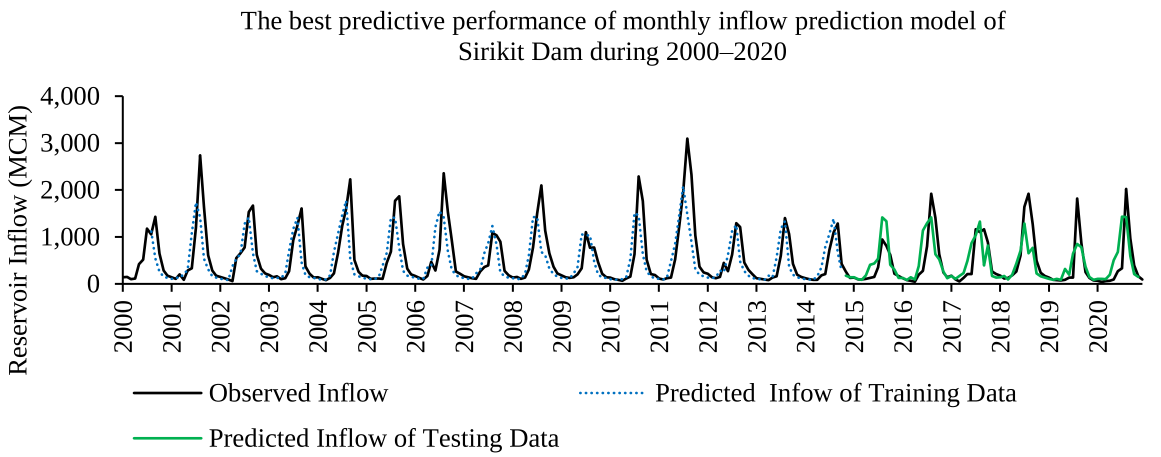

Figure 8 The qualitative comparison between observed and predicted inflows of the best monthly prediction model with model parameters: Training–Testing Ratio: 70:30, Inputs: Inflow t, Avg. Inflow t–1 to t–7, Precipitation t, Learning Rate: 0.001

4. CONCLUSIONS

XGBoost which is a tree–based ensemble machine learning algorithm, was used to predict the daily and monthly reservoir inflows of the Sirikit Dam, Thailand. Training and testing the prediction models were implemented using observed inflow and climate data during 2000–2020 as the key prediction inputs. The XGBoost model presented more reliable and robust prediction results especially for the daily prediction model with the highest R^2, R, NSE and small values of RMSE and MSE. It is found that the predictability of the XGBoost model to predict the daily reservoir inflow with good precision is strongly higher than the monthly inflow. Predicting the average values of the daily and monthly inflows gives the prediction results definitely closer to the observed inflows. However, the capability to characterize and predict the dynamics of extreme values of these two developed models is still weak. Therefore, to improve the quality of machine learning algorithm for hydrological prediction, the model parameters need to be optimized. In addition, conducting the further study using the technological advancement of machine learning is highly encouraged for the achievement of hydrological forecast on water resources management.

5. ACKNOWLEDGMENTS

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Water Supply and Sanitary

RISK AND VALUE-BASED ANALYSIS IN WATER DISTRIBUTION SYSTEM: CASE STUDY OF MWA'S LADPLAO BRANCH

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ABSTRACT

Water loss has been the main challenge of the Metropolitan Waterworks Authority (MWA) for over a decade; 31.25% loss took place in 2020. To address this challenge, MWA has paid attention to investing in a pipe replacement scheme. However, the recent projects cause a high expenditure while the water loss still has a trend to increase significantly. The difficult obstacle is how to efficient use of limited budgets with the appropriated need of pipe replacement. This study aims to prioritize pipeline replacement based on two indices, Risk Index (RI) and Infrastructure Value Index (IVI), and to describe the relationship of those indices in specific areas of different characteristics. Moreover, the analysis of pipe replacement in the last three years was investigated its effectiveness of selection in this study. The Ladplao branch was employed as a study area. Its water distribution system (WDS) has a polyvinyl chloride pipe (PVC) with a length of approximately 2,350 kilometers in 64 district metering areas (DMA) and with average pipe aging of 35 years. Five different characteristic DMAs depending on their specific data were selected for the study.

To analyze RI, three crucial parameters, namely, length, age, and historical leakage data, were considered via fuzzy logic inference. For asset valuation, the approach of asset-oriented technique was implemented to evaluate the infrastructure value. First, the unit costs were used to determine the existing asset replacement costs, then the current infrastructure values and its replacement cost was calculated for the IVI. Finally, a modified Risk-Value Index (MRVI) was adapted to prioritize pipe routes. It was found 17,669.84 meters of pipe length in 29 pipe routs that RI is over 50 % by indicating high risk of distribution pipeline, and 25,901.29 meters of 200 pipelines that have IVI value lower than 0.4 from 10 DMAs. It means that many poor condition pipes had not been yet arranged in replacement priority. However, discussing these indices regarding the various conditions points to critical issues that still require to be addressed.

Keywords: Asset valuation, District metering area, Fuzzy inference system, Infrastructure value index, Risk index.

1. INTRODUCTION

Metropolitan Waterworks Authority (MWA) is the state enterprise responsible for producing a safe water supply in urban areas, covering Bangkok, Nonthaburi, and Samut Prakarn Provinces, as shown in Figure. 1. The serviced area of 2,418 square km is divided into 18 branches under a 190 km transmission system, 1,732 km main trunk system, 32,754 km distribution pipes, 4 water treatment plants, and 10 pumping stations, supporting sufficiently fresh water to approximately 2.5 million customers. However, the water distribution pipes are aging infrastructures, with serious concerns emerging. Therefore, in 2018, MWA commenced a new project to invest in a pipe replacement. As a result, the water distribution pipes were replaced by approximately 1,000 km, 1,280 km, 1019 km, and 1065 km from 2018 to 2020.

Though these recent projects have caused high expenditure, the water loss still has a significant trend, which remains approximately 30% nowadays. The problematic obstacles are how to efficient use of limited budgets with the appropriated need of pipe replacement.

In the conventional method of pipe selection, the scoring pipes with several factors such as pipe age, materials, and pipe length are applied with the condition rating. It was utilized as the first alternative for many projects of MWA over decades. However, in recent years, two key approaches have played an important role in the underground infrastructure assessment, i.e., the risk assessment associated with the probability of failure and uncertainty, and the asset valuation related to asset management focuses on the infrastructure condition in terms of economics.

Much evidence regarding water supply risk assessment is reported in the literature, and risk assessment methodology is adapted in different fields. The diversified task of water supply pipeline, namely the designing, constructions, and operation management as the open environment, can be predicable to find out its critical hazards. It is reported in detail, respecting some water supply pipeline risk assessment methodologies and risk assessment methods in different works as risk index (RI).

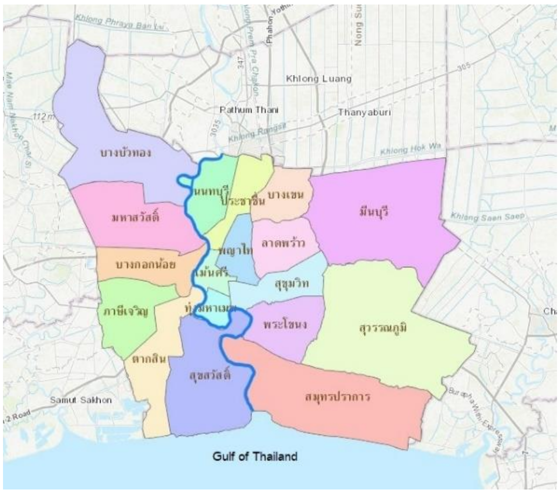


Figure 1 MWA's serviced area in 18 branches

Li et al. [1] developed a quantitative risk assessment method associated with a fuzzy logic method for a long-distance water transmission pipeline (LDWTP) to avoid and recognize risk before taking place. It was proposed to provide the confidence that the water supply project can operate as usual. Alidoosti et al. [2] adapted the fuzzy set theory to model the uncertainty for assessing the security risk of pipeline systems with Risk Analysis and Management for Critical Asset Protection (RAMCAP); the results presented a more accurate risk analysis to protect the critical assets in the pipeline system. Moreover, Ercole et al. [3] proposed the integrated solution as the analysis model for rehabilitation planning of water distribution networks. The application included the network reliability and risk assessment to evaluate at a nodal level under the economic constraints.

Over the last few years, a fuzzy logic-based inference system (FIS) is the most efficient approach to achieve risk assessment in several research fields. According to Yazdani [4], FIS was used to assess the tunnel risk events during construction. It provided the existing risk of project related to underground uncertainties and prioritized them for the effective measures to eliminate risk in their project. In 2007, Wang et al. [5] introduced the Adaptive Neuro- Fuzzy System (ANFIS) methodology to bridge risk assessment for Highway Agencies to deal with real-time risk. Christodoulou et al. [6] also suggested the neuro-fuzzy decision-support system with Artificial Neural Network (ANN). It deployed the data as the analytical and numerical techniques to generate a multi-forced risk-of-failure analysis for evaluating the main breaks in the water distribution system of the urban area.

FIS has played an important role in analyzing and assessing risk in many risk measurements [7]. For example, fuzzy set theory and analytic hierarchy process have been integrated to calculate the water distribution failure risk [8]. Additionally, two factors that resulted in the existing uncertainties are physical variability and lack of knowledge [7]. Thus, many researchers attempt to improve fuzzy set theory in many solutions for decreasing uncertainties in technical terms.

A blend risk index was proposed to reduce the number of conditions in the rule base [10]. This technique separated four significant factors; Age, Length, Leak, and Depth, in two partial FISs, and then two membership functions were calculated with thirty rule bases in each partial FIS. The blend fuzzy inference system received the output of each partial FIS as input and returned the overall risk index of the water distribution system. This approach can reduce the massive rule bases from 900 to 85, compared to conventional fuzzy logic.

For asset valuation, the prioritization of investment is the main concept of asset management. Infrastructure Value Index (IVI) was proposed as a value-based asset condition index for infrastructures. It broadly proved and developed through a decade [11], [12]. Additionally, IVI was often used to asset the water infrastructure in various projects in the water sector. [13], [14].

In this paper, the study intends to combine two indices in terms of risk and asset valuation for water distribution system assessment. The objective of the proposed work is two-fold: (1) to reveal adapted technique for prioritizing water distribution pipeline replacement in each isolated area; (2) to express the role of each area characteristics on those indices for launching the possible measures to deal with each different area as strategic planning.

2. METHODOLOGY

This study comprises two main components; Risk assessment and Asset valuation. Figure 2 shows a diagram covering the whole procedures of the study framework. The first step is data collection, i.e., three main parameters, such as pipe length, pipe age, and historical leak, were gathered from Geographic Information System (GIS) for risk assessment. At the same time, the unit cost was compiled from MWA's cost estimating database division for asset valuation. Then, the fuzzy logic toolbox in MATLAB version R2021a was applied to determine RI for the risk assessment procedure. Similarly, asset valuation was calculated through an asset-oriented approach for IVI values. In the analysis step, previous pipe replacement was investigated for the effectiveness of pipe selection in terms of risk via recalculation of RI. Then, Modified Risk-Value Index (MRVI) was generated for pipe prioritization, and pipe replacement strategic planning resulted from the combination of RI and IVI. Lastly, two similar area groups will be used for model testing.

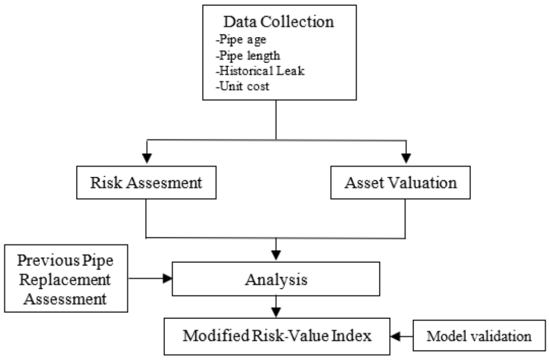


Figure 2. Modified Risk-Value Index Diagram

2.1 Fuzzy logic model for water distribution risk index

In this paper, FIS that the membership function regarding the if-then rule and fuzzy logic operator was set as Mamdani fuzzy inference system. This FIS is plain, and its rule designing is efficient and straightforward. FIS comprises four steps: (i) fuzzification, (ii) knowledge base, (iii) inference engine, and (iv) defuzzification, as shown in Figure 3.

(i) Fuzzification: The process uses the membership function to originate fuzzy values from input data that composes three crucial input data; pipe ages, pipe length, and historical leak, as shown in Figure 4. Several membership functions can be used in Mamdani FIS (Gaussian, trapezoidal, z-shape, etc.). In this study, the triangle membership function was adapted to all variables, while the sigmoid membership function was used in some membership functions of the leak variable. Figure 5 demonstrates the membership functions of each variable.

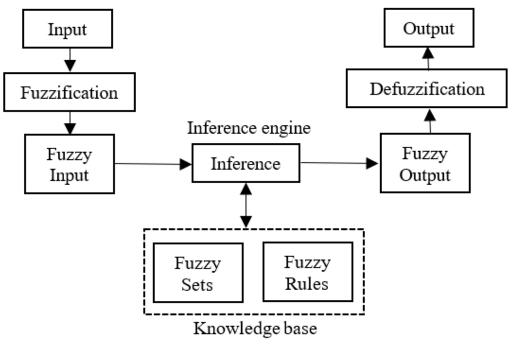


Figure 3 Structure of Mamdani FIS

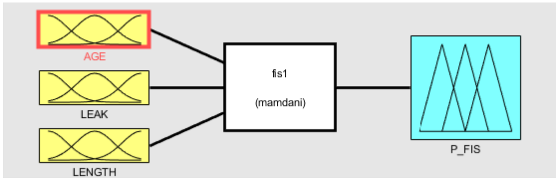
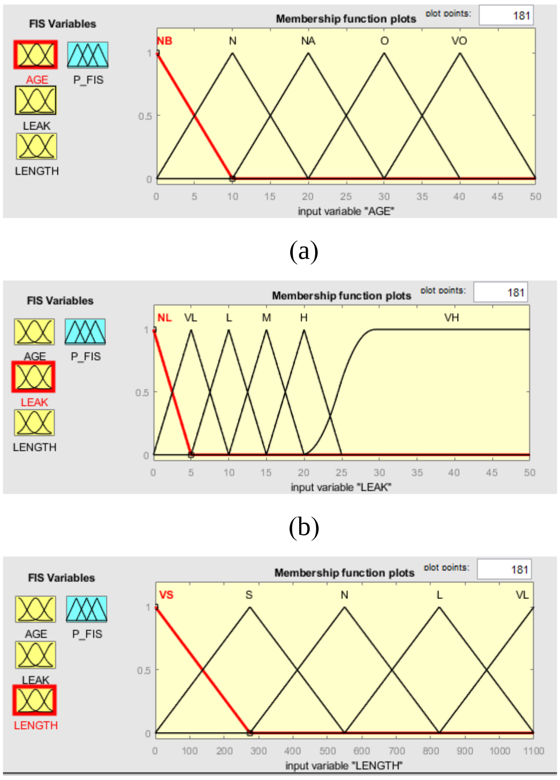


Figure 4 The architecture of FIS



(a)

(b)

(c)

Figure 5 The membership function: (a) Age, (b) Leak and (c) Length

Eq. (1) formulas are the triangle membership function that needs only three parameters (a, m, b) to be determined. These parameters represent the lower limit, the upper limit, and a value, respectively, where a < m < b and x is the actual value.

$$\mu_A(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{m-a} & a < x \leq m \\ \frac{b-x}{b-m} & m < x < b \\ 0, & x \geq b \end{cases} \quad (1)$$

The sigmoid membership function is given by Eq. (2) as follows:

$$f(x', a_k, c_k) = \frac{1}{1+e^{-a_k(x-c_k)}} \quad (2)$$

where:

$$a_k = (\ln(0.9) - \ln(0.1))(c_k - \beta) \quad (3)$$

x' is numeric, complex, or vectors with values to fuzzification, c_k is the acceptable value that has the value in range 0 and 1, β is the value almost unacceptable in range 0 and 1.

(ii) Knowledge base: this step evaluates rules and linguistic variables based on the fuzzy set theory for calculating estimated reasoning. Table 3 shows the linguistic variable of all input data providing 150 rule bases. The fuzzy set of age are defined as Very Old (VO), Old (O), Normal Age (NA), New (N), Brand New (BN). Similarly, six fuzzy sets are defined for the input variable leakage: No Leakage (NL), Very Low (VL), Low (L), Medium (M), High (H) and Vary High (VH). Five fuzzy sets are defined for input variable length: Very Short (VS), Short (S), Normal (N), Lengthy (L), and Very Lengthy (VL). Lastly, the output variables are defined as follows: Very Low (VL), Low (L), Medium (M), High (H) and Very High (VH). The output of FIS is the final risk index value of the fuzzy logic model. Moreover, the average rule-based rule as shown in Eq.4 was applied so that rule specification:

$$AVG. = (MF1 + MF2 + n \ldots)/n \qquad (4)$$

where n is the number of membership functions. For instance, the output of the rule is specified as:

AVG.= (3+3+1)/3 = 2.33 = Low

(iii) Inference engine: the input fuzzy sets, e.g., pipe age, pipe length, and the historical leak, will be mapped within this step into fuzzy output set as a risk. It performs the inference operations on the rules.

(iv) Defuzzification is the step to convert the fuzzy results as input and generate numerical values through the center-of-gravity method. Figure 6 presents the output variable in 5 linguistic variables that have values from 0 to 1: VL (≤0.25); L (0-0.5); M (0.25-0.75); H (0.5-1); VH (≥0.75).

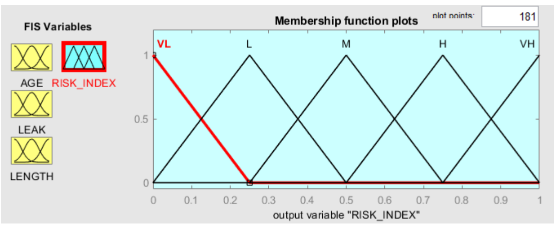


Figure 6 The output variable

2.2 Infrastructure value index for asset valuation

The primary purpose of asset valuation is to establish the rehabilitation priorities of infrastructures in the short term and analyze various rehabilitation strategies for maintenance in the long term. IVI is widely employed as the key performance index for reflecting the degree of infrastructure aging consisting of different assets. It is a ratio between the current value of infrastructure and the replacement cost on the modern equivalent asset. IVI formula is defined as follows [11]:

$$IVI(t) = \frac{\sum_{i=1}^{N}\left(rc_{i,t} \cdot \frac{rul_{i,t}}{eul_i}\right)}{\sum_{i=1}^{N} rc_{i,t}} \qquad (5)$$

In which *t* is the year of the assessment; *N* is the total number of the assets; $rc_{i,t}$ is the replacement cost of the asset *i* in year *t;* $rul_{i,t}$ is the residual useful life of the asset *i* in year *t*; eul_i is the expected useful life of the asset *i*.

This indicator has theoretical values between 0 and 1, and it has been identified in four interval values that can express the characteristics of the infrastructure. Table 1 represents the infrastructure characteristics of IVI interval values.

Table 1 Infrastructure characteristics with IVI values

IVI interval	Infrastructure characteristics
IVI ≥ 0.60	– Young infrastructure not yet stabilized. – Infrastructure that although already old are in a growth phase. – Infrastructure where there is a high investment in rehabilitation.
IVI= [0.45;0.60]	– Infrastructure still in good condition.
IVI= [0.30;0.45]	– Poor infrastructure condition. Needs rehabilitation investments.
IVI < 0.30	– Ageing infrastructure. Needs significant investments in rehabilitation.

In this study, the expected useful life is 50 years, which is the design life of MWA's water distribution pipe design criteria. Table 2 demonstrates the unit price of each pipe size as the replacement cost.

Table 2 Pipe unit cost for replacement in 2020

Pipe size (mm)	Unit price/meter (Baht)
100	1588
150	2137
200	3038
300	5175
400	7000

2.3 Modified risk-value index

This index is the combination of RI and IVI development. The high RI value means the pipes reach having the opportunity to leak while the low IVI value indicates the poor condition of the infrastructure, so the broad range of these indices

Table 3 Variables linguistic with weights and outputs linguistic (Number values not including Risk Index)

Numeric values	1	2	3	4	5	6
Age	Very Old	Old	Normal Age	New	Brand New	
Leak	No Leakage	Very Low	Low	Medium	High	Very High
Length	Very Short	Short	Normal	Lengthy	Very Lengthy	
Risk index	Very Low	Low	Medium	High	Very High	

can describe the worse criteria of the pipes. To pipe prioritization, each pipe will be found out the differential of the indices (RI-IVI), and then the normalization method will be applied for pipe prioritization as shown in Eq. 6. The highest value of MRVI is 1, representing the first priority to be replaced, while 0 is the value of the last development.

$$MRVI_i = \frac{norm_i - norm_{max}}{norm_{max} - norm_{min}} \quad (6)$$

$$norm_i = RI_i - IVI_i \quad (7)$$

$norm_{max}$ is the maximum value of norm in the total asset; $norm_{min}$ is the minimum value of norm in the total asset.

3. Study Area

3.1 Ladplao Branch

As shown in Figure 1, the Ladplao branch is located in the middle of the entire service area. There is 2,350 km. of pipe length covering 176,262 customers in 64 District Metering Areas (DMA), as shown in Figure 7. In addition to the residential customer, industry and government are the key customers of this branch. Ladplao has a cumulative water loss of 23 % compared with MWA's average at 31.25% in 2020. However, many DMAs still encounter high water loss; 10 DMAs have water loss greater than 40%, and 19 DMAs have water loss of 30% to 40%. Thus, this branch has been selected as the case study for various reasons such as the diversification of customers, area characteristics, and the difference in the water loss rate.

3.2 Study areas selection

To investigate the effect of area characteristics on the modified index and the model validation, 10 DMAs in 5 different area types were classified by group A and group B, not different in their characteristics, as elaborated in Table 4 and Table 5. There are three considerable criteria for identifying characteristics in this study;

(1) Average water leakage rate: High Water Leakage (HWL)

(2) Pipe density: High Pipe Density (HPD) and Low Pipe Density (LPD);

(3) Water usage: High Water Usage (HWU) and Low Water Usage (LWU).

4. Experimental Results and Discussion

4.1 Experimental results

The dataset used to input in FIS comprises three actual parameters: age, length, and historical leak provided by MWA's GIS system. In this study, the pipelines in 10 DMAs with five different area characteristics were assessed to quantify each pipeline's RI in this experiment.

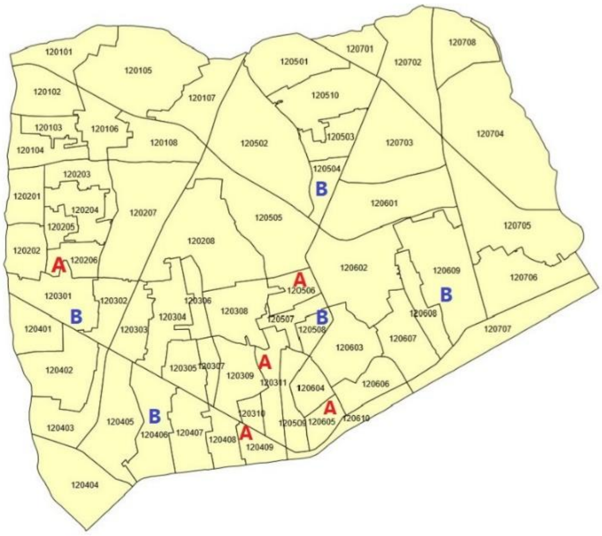


Figure 7 DMA of case study

Figure 8 reveals the seven high-risk pipe routes of HWL-A from 433 routes in 27,891.35 meters that the RI value is identical or greater than 0.5 and its IVI values. The result shows all high-risk pipe routes of the highest water loss DMA that should be replaced at 4,360.38 meters of pipe length instantaneously. The highest RI value is 0.75 in HWL-A5; the IVI is slightly greater than 0.45, while the lowest value of IVI is HWL-A2 at 0.3 with 0.625 of RI value.

Table 4 Area characteristics of group A

AREA TYPE	DMA	CUSTOMERS (1)	PIPE LENGTH (m) (2)	PIPE DENSITY (2) / (1)	WATER USAGE cum/day/person	Avg. %WL
HWL-A	120206	2193	27893.88	12.72	1.12	51.96
HPD-A	120311	4348	33724.79	7.76	1.18	31.00
LPD-A	120605	251	5980.4	23.83	8.54	10.59
HWU-A	120409	989	13439.73	13.59	4.78	5.52
LWU-A	120506	2195	27181.05	12.38	0.78	27.65

Table 5 Area characteristics of group B

AREA TYPE	DMA	CUSTOMERS (1)	PIPE LENGTH (m) (2)	PIPE DENSITY (2) / (1)	WATER USAGE cum/day/person	Avg. %WL
HWL-B	120301	4236	49797.49	11.76	1.28	45.19
HPD-B	120508	5248	51536.9	9.82	0.94	18.81
LPD-B	120609	1220	35619.23	29.20	1.46	11.00
HWU-B	120406	3159	46600.08	14.75	2.38	32.96
LWU-B	120504	836	9475.5	11.33	0.97	32.94

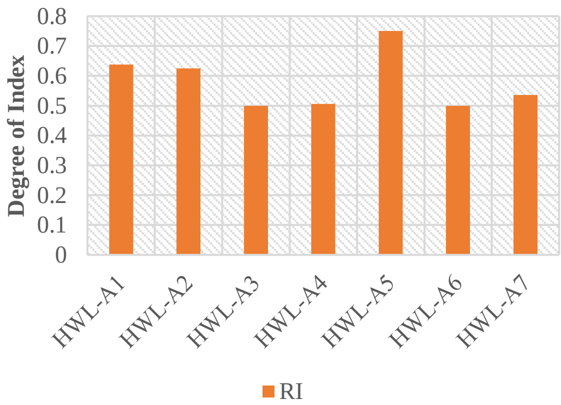


Figure 8 High-risk pipe base on RI comparing with IVI.

In terms of asset condition, Figure 9 presents the poor pipes based on IVI and its RI values. Although all these 15 pipe routes have deterioration pipe that IVI is lower than 0.45, it has a low risk of leakage. However, the length of low IVI pipes is 578.65 meters, so the risky pipe length combined with high RI pipes results in 4939.03 meters needing to be replaced.

From these two indices, planners cannot make an effective decision to choose the appropriate pipe route via only one perspective, so the MRVI is used as a tool to support the choosing decision. For example, Figure 10 exhibits the prioritization of risky pipes in HWL-A via MRVI. HWL-A2 is the most considerable route to change pipes immediately, although its RI is less than HWL-A5 and the RI value is the highest in this area. Meanwhile, there are four routes in the last prioritization that MRVI is zero.

To validate the assumption regarding the effectiveness of previous pipe replacement on the water loss rates, all pipes replaced within three years were back-calculated which the age and historical leak dataset were changed to be 22 years, based on the actual information. Table 6 manifests the data of 8 various DMAs that pipes were replaced in the last three years. It also presents the number of high RI values in 2017 and 2020 resulting from modelings. In addition to LPD-A and LPD-B, in which the high-risk pipes decreased, there are 2 DMAs that the number of risky pipes increased, and the water loss rate tends to rise significantly in all left DMAs from 2017.

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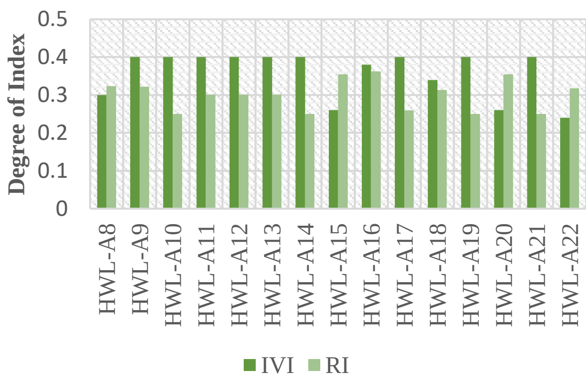

Figure 9 High-risk pipe base on IVI and RI

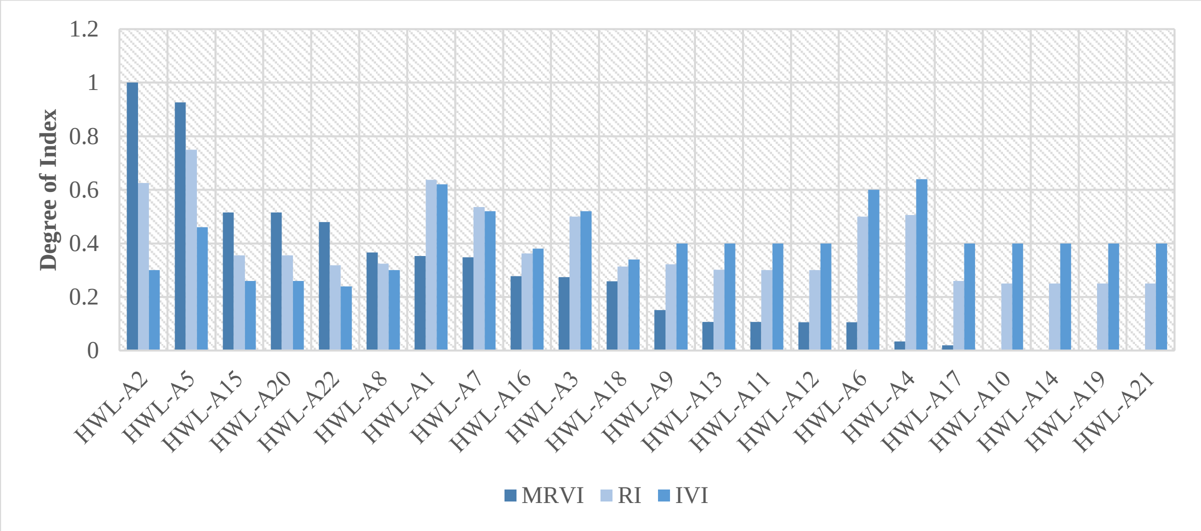

Figure 10 Pipe prioritization of HWL

Table 6 The recalculation of RI for previous pipe selection validation

Area Type	WL (%). 2017	WL (%) 2020	No. routes (Replace)	Length (Replaced)(m)	2017(RI)	2020(RI)
HWL-A	33.73	51.95	72	2341.51	6	7
HWL-B	17.44	46.07	22	1103.5	2	2
HPD-B	6.31	18.71	3	179.14	1	1
HWU-A	5.11	5.52	1	36.73	2	2
HWU-B	40.77	48.19	9	609.9	7	9
LWU-A	12.99	27.61	34	3800.23	1	1
LPD-A	18.43	10.61	69	2506.71	1	0
LPD-B	11.94	10.07	3	884.06	1	0

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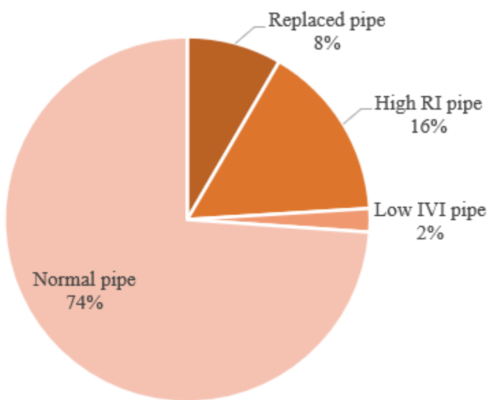

Figure 11 HWL-A's pipe proportion in 2020

Likewise, Figure 11 represented the pipe proportion of RI and IVI of HWL-A after the replacement. There was 8% of replaced pipes through last three years that is inaccurate replacement pipes to advocate reducing water loss rate. It is still 18% of pipes length comprised of high RI pipes and low IVI pipes disregarded due to the conventional selection approach. Thus, it leads to a dramatic rise in water loss rate, as shown in Figure 12.

Contrastingly, there is a substantial decrease in water loss rate in LPD-A by roughly 8%, as shown in Figure 12. Figure 13 shows LPD-A's pipes were replaced 42% in 69 routes. This good performance resulted from the replacement pipes via the conventional approach to eliminate high RI routes and low IVI routes within three years.

However, 2,506.71 meters in 69 routes of changed pipes has sounded an ineffectiveness to investment from the conventional approach because the recalculation outcomes demonstrate only a route of 330.87 meters that has the opportunity to leak due to the high RI value of 0.56. If the right pipeline is specified since 2017, the water loss rate can be obtained both positive and negative results because the deteriorated pipes were not detected; namely, it was found out just the high risky pipe.

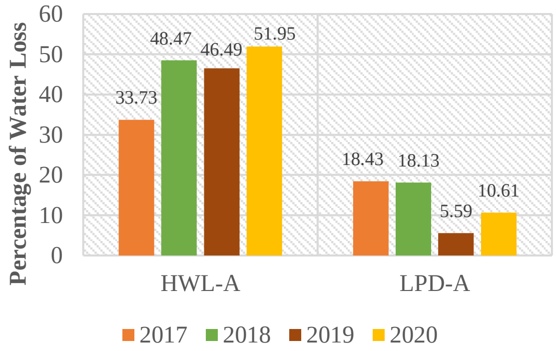

Figure 12 Comparing water loss rates of HWL-A and LPD-A from 2017 to 2020

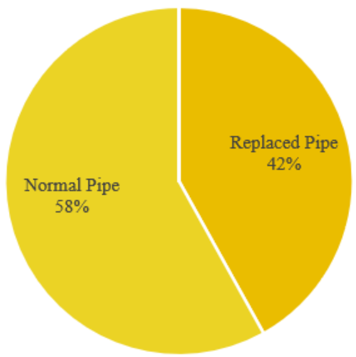

Figure 13 LPD-A's pipe proportion in 2020

Consequently, replacement pipes without considering RI and IVI cause an ineffective investment and are impractical to water loss reduction as LPD-A and HWL-A, respectively.

Moreover, it was found that some areas that were having high water loss rates were not considerably prioritized. For example, HPD-A that the 5,021.46 meters of pipe length comprised high-risk pipe and deteriorated pipe condition was not paid attention to be replaced.

For strategic planning, the area groups are arranged with the average MRVI values of each area, as shown in Figure 14. It can separate MRVI values into two levels; the first level of the average MRVI is greater than or equal to 0.4, consisting of HWL-A, HWL-B, HPD-A, and HWU-A. The second level is the group of HPD-B, HWU-B, LWU-A, and LPD-A. All average MRVI values of each area were calculated by Eq. 6 and Eq. 7 without the limited areas. The former level can be first implemented to plan the pipe replacement project or can be classified areas to deal with separately. This measure may reduce the leak rate of deteriorated pipes obviously because the planners can focus on the riskiest area. For example, if all routes of HWL-A are improved, it will be better than enhancing the pipes from high to low MRVI values as the sequences since to do this cannot provide a substantial positive impact on the leakage rate.

Nevertheless, this measure was considered without other factors, e.g., water loss rate and pipe length. Table 7 displays the MRVI's component of each area. Thus, the outcomes can quantify the risky-pipe routes and their length that can be used to reinforce the planner decision for selecting the critical routes.

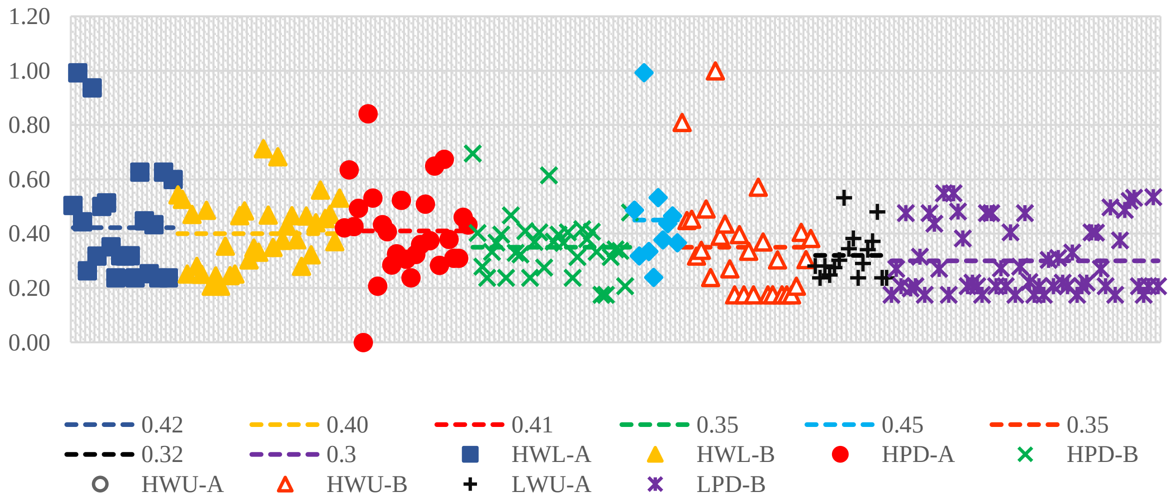

Figure 14 Area group prioritization for strategic planning

Table 7 The pipe expected length of replacement resulted from MRVI

NAME	AREAS	DMA	HRI		LIVI		MRVI	
			Route	Length (m)	Route	Length (m)	Route	Length (m)
HWL	HWL-A	120206	7	4,360.38	15	578.65	22	4,939.03
	HWL-B	120301	2	1,158.64	33	3,557.78	35	4,716.42
HPD	HPD-A	120311	6	3,473.19	21	1,548.27	27	5,021.46
	HPD-B	120508	1	561.99	33	3,777.58	34	4,339.57
HWU	HWU-A	120409	3	2,088.64	7	1,558.61	10	3,647.25
	HWU-B	120406	9	5,418.27	19	1,643.94	28	7,062.21
LWU	LWU-A	120506	1	608.72	15	1,345.86	16	1,954.59
	LWU-B	120504	0	-	0	-	0	-
LPD	LPD-A	120605	0	-	0	-	0	-
	LPD-B	120609	0	-	57	11,890.60	57	11,890.60
	Sum		29	17,669.84	200	25,901.29	229	43,571.13

4.2 Discussion

MRVI is a modified index to originate the model for prioritization of water distribution pipes replacement. Group A and B in each characteristic were chosen for model testing. In Table 7, the results illustrate the comparison of outcomes between group A and group B provided the length of the expected pipes to replace in positive correlative.

This index focuses on the risk of pipes typically brought as indicators for choosing the high-risk pipe to break and considering the asset value associated with the deterioration rate and pipe life.

In pipe prioritization within each DMAs, MRVI can also arrange for all DMAs to replace their pipe as a sequence for strategic planning, as shown in Figure 14. This approach leads to advantages in focusing on the high-water loss rate or dealing with the limited investment cost depending on the organization policy. However, implementing this approach for strategic planning, other criteria should simultaneously be contemplated. For example, a high MRVI value means that DMA is the priority to deal with, but its water loss rate is the lowest. Thus, this DMA should be switched to be the last DMA for replacement, as HWU-A in Figure 14. This case is a large number of high MRVI values and smaller replacement pipe routes in this DMA.

However, it was found that although LWU-B has a water loss rate of almost 33%, pipes in this DMA are never replaced through the last three years and not found its both high RI and low IVI values. Thus, it can imply that the high-water loss rate results from other factors, i.e., valve chamber of transmission pipes that water can flow from the tunnel into the main pipe is located in this area so it can cause the high-water input volume during the calculation of water loss rate.

This study also found that groups of high characteristics (HWL, HPD, and HWU) have an increasing trend to find the high-risk pipes and poor condition. Nevertheless, the relationship between the five distinct types and pipe replacement for reducing water loss rate is unclear.

5. CONCLUSIONS

The current paper aims to combine two reasonable indexes based on risk assessment, including asset valuation, to prioritize water distribution pipe within each DMA. It adopted the strategic planning resulting from the effort to reduce the high water loss rate with the effective investment for rehabilitation projects within the constraint budget.

10 DMAs in five different characteristics from the Ladplao branch were selected as the study areas. These five characteristics were classified by three criteria, e.g., the average cumulative water loss, the pipe density, and the average water usage. Furthermore, three parameters were gathered from GIS; pipe length, pipe ages, and the historical leak as a data set. FIS was used to quantify RI for the risk assessment. Besides, the unit cost was utilized as the input data of IVI to evaluate the asset valuation with an asset-oriented approach. This index provides the present condition of each pipe, resulting in the understanding of planners for deciding short and long-term planning projects.

To combine the indices, RI and IVI were modified called MRVI. It has proven to be the effective index to prioritize the deterioration pipe that can support planners in selecting the weak pipe correctly. However, implementation of MRVI in strategic planning should be applied with other criteria such as water loss rate. Moreover, the measure to classify area characteristics should be the first deal for management to reduce water loss rate through pipe replacement approach.

Future work will include more parameters such as pipe depth, pipe material, and the above surface to input data in FIS. Again, a service-oriented approach should be used for asset valuation with IVI.

6. ACKNOWLEDGMENTS

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Risk and Disaster

THE FLOOD WARNING INDICATORS ASSESSMENT USING STREAM FLOW AND SATELLITE IMAGE DATA

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ABSTRACT

Sisaket and Ubon Ratchathani provinces are in a downstream of the Mun river. There is often a big flooding in these provinces, especially Ubon Ratchathani province as in 1977, 2002, 2010, and 2019. Then, it is important to consider flood warning because these provinces have not the flood warning. The purpose of this study is to evaluate water levels and discharges in the runoff stations for the flood warning indicators in Sisaket and Ubon Ratchathani provinces based on the 137 satellite images. To access the purpose, all satellite images are in the process of image processing to determine a flooding area by using the ERDAS imagine software. Water mask is generated by using the digitization technique. Thresholding technique is considered to segregating the water area and non-water area from satellite images during flooding time. Then, the flood mapping is done by overlaying the inundated layer on the sub-district boundary map. Thereafter, each satellite image is classified flooding area by sub-district in each province. On the other hand, water level and discharge in the same day with all 137 images are matching to determine the maximum, mean, and minimum of water level and discharge. The minimum values are the beginning of flooding. The mean values present a serious flood situation. The maximum values are a very serious of flooding or a big flooding. The runoff stations where can evaluate the flood warning include M5, M9, M182, M7, M179, M170, E.20A, and E.98. The advantages of flood warning indicator are (1) using original tools at runoff station, (2) low-cost operation and management (3) easy for understanding and using, and (4) that new data is not collected. The disadvantages are (1) a static flood warning and (2) that rainfall is not input data.

Keywords: Flood warning indicator, Stream Flow, Satellite Image, Ubon Ratchathani, Sisaket

1. INTRODUCTION

Flooding is a natural phenomenon that is occur from a high rainfall. It leads to a more runoff over the surface and flow to the rivers more than usual. If the river is unable to get all the water flowing into the river, it will have a higher water level than bank. Then, the water will overflow on both sides of the river and flow out into a wide area. In addition, in lowlands and community areas where there is no complete drainage system, if there are the prolonged heavy rains, it is a causing of flooding. A flooding can have far reaching effects on people and the environment. [1]–[4]

In present, satellite images are applied to concern the effect of flooding areas because it can collect data in the large areas. The advantages of satellite image are a spatial and temporal resolution. There are many types of satellite images. For example, the ALOS/PALSAR satellite was used to extract the flood inundation in Okazaki City and Anjo City [5] and to create a flood hazard mapping [6], Landsat was applied for water body detection [7,8] and flood hazard mapping [9,10], COSMO-SkyMed constellation was contributed from flood mapping to earthquake damage assessment [11], Sentinel-1 was used to monitor flooding in the Ebro River [12], Sentinel-2 was concerned to evaluate the catastrophic flood in the West Mediterranean [13], and RADARSAT image was applied to determine a maximum flood prone area in Kelantan River Basin. [14] Moreover, ALOS-2 can be combined with hydrodynamic simulation data to detect a flooding area. [15] Then, the data from the many types of satellite images can integrate to consider the flood hazard, flood inundation, flood risk, and flood warning indicators.

In Thailand, Mun river is a big river and flow through many provinces. The Sisaket and Ubon Ratchathani provinces are in a downstream of the Mun river. Then, there are often a big flooding in these two provinces, especially Ubon Ratchathani province as the big flooding in 1977, 2002, 2010, and 2019. Moreover, there are flooding in every year at Warin Chamrap district, Ubon Ratchathani province. To protect flooding in Mueang Ubon Ratchathani district, the water barrier flap was constructed along the Mun river, but the flood warning system is not set up. Also, there is a shortage of data analysis leading to the flood warnings in these provinces although there are many runoff stations along Mun river. The flood warning is an important system as in many research and in many countries. This system can reduce the effect of flooding on people and the environment. [16]–[18]

The objective of this study is to evaluate water levels and discharges in the runoff stations for the flood warning indicators in Sisaket and Ubon Ratchathani provinces based on the satellite images data. The history data of both satellite images and stream flow data are applied to classify the relationship amount of water level, discharge, and flood area. This is a new concept for flood warning in Thailand and this is not difficult to apply in other areas.

2. DATA USED

2.1 Satellite Images

To concern flooding area using satellite images for this study, they are consisted of ALOS (1 image), COSMO-SkyMed-1 (20 images), COSMO-SkyMed-2 (15 images), COSMO-SkyMed-3 (7 images), COSMO-SkyMed-4 (16 images), LANDSAT-5 (3 images), RADARSAT-1 (10 images), RADARSAT-2 (50 images), Sentinel-1 (15 images) and Sentinel-2 (1 images). These 137 satellite images can be downloaded on the website of The Geo-Informatics and Space Technology Development Agency (Public Organization) or GISTDA. The characteristic of each satellite images is following.

ALOS stand for the Advanced Land Observing Satellite. It is scheduled for launch by the Japan Aerospace Exploration Agency (JAXA) in JFY 2004. There are three remote sensing instruments: an L-band polarimetric Synthetic Aperture Radar (PALSAR), an along-track 2.5-meter resolution stereo mapper (PRISM) and a 10-metre multi-spectral scanner (AVNIR-2). PALSAR utilization is primarily focused on terrestrial applications, in particular global monitoring of forest and wetlands and crustal deformation measurements, as well as DEM generation, disaster monitoring and geological resources surveys. [19]

COSMO-SkyMed stand for the Constellation of Small satellites for Mediterranean basin Observation. It is an Italian Earth Observation Dual-Use (Civilian and Defense) Space System for global environmental monitoring, scientific and commercial purposes, and strategic applications (Defence and National Security). [20] The Cosmo-SkyMed satellite system is a constellation of radar-type satellites (SAR) with the same characteristics. There are 4 satellite in the Cosmo-SkyMed satellite system that are COSMO-SkyMed-1, COSMO-SkyMed-2, COSMO-SkyMed-3, and COSMO-SkyMed-4. The Cosmo-SkyMed satellite is suitable for civilian and military affairs. The main purpose is to track global changes in urgent emergencies, policy planning, and scientific research studies. A wide range of information is available to suit your specific tasks. Both of Multi-polarimetric and multi-temporal data are appropriate for many types of civilian and defense tracking. [21]

LANDSAT-5 is a low Earth orbit satellite that managed by U.S. Geological Survey (USGS) and National Aeronautics and Space Administration (NASA). LANDSAT-5 supplies images of the Earth's surface in seven spectral bands, of which six cover the visible and shortwave infrared part of the electromagnetic spectrum and one the thermal infrared "emissive" part of it. This satellite has a mission for providing the image of Earth's land surface that can be applied for the decision of natural resources and environment. [22]

RADARSAT is a Canadian remote sensing earth observation satellite that managed by the Canadian Space Agency (CSA). There are three programs consisted of RADARSAT-1 (1995-2013), RADARSAT-2 (2007-now), and RADARSAT Constellation. The objective of RADARSAT-1 is to produce a satellite for earth observation by way of a Synthetic Aperture Radar that is an advanced radar sensor and powerful microwave instrument. RADARSAT-1 is helpful for commercial and scientific users. RADARSAT-2 is a one of the most advanced radar images in the world. It is an improvement version of RADARSAT-1 that increase spatial resolution, multiple polarization filters, solid state recorders, and GPS receivers on board. RADARSAT constellation is a construction to make the improvement of RADARSAT-2. The mission of RADARSAT constellation is to aids with disaster management as well as monitor ecosystems. [23]

Sentinel is developed by the European Space Agency (ESC). There are six programs in Sentinel consisted of Sentinel-1, Sentinel-2, Sentinel-3, Sentinel-4, Sentinel-5, and Sentinel-5P. For this study, Sentinel-1 and Sentinel-2 are concerned to determine flooding area. The mission of Sentinel-1 is normally to observe land and ocean. It is composed two polar-orbiting satellite operating day and night and perform radar imaging, enabling them to acquire imagery regardless of the weather. On the other hand, Sentinel-2 is for land monitoring and composing the two of polar-orbit satellites to prepare a high-resolution optical imagery such as vegetation, soil, and coastal areas. [24]

2.2 Stream Flow

Stream flow data in each runoff station is also important data to determine the relationship between water level/discharge and flooding area. Stream flow data consist of water level (meter mean sea level: m MSL) and discharge (cubic meter per second: cms.). The runoff stations include M5, M9, M182, M176, M7, M179, M179A, M170, M69, E20A, and E.98. These runoff stations are in Sisaket province, Ubon Ratchathani province and Yasothon province where the Chi River flow to Mun river in Ubon Ratchathani province. The data duration is at the same time with 137 satellite images (Sep. 26, 2010, to Oct. 5, 2019).

3. METHODOLOGY

To evaluate water levels and discharges in runoff station for the flood warning indicators in Sisaket and Ubon Ratchathani provinces based on satellite images and stream flow data, the process of this study is following.

1. All 137 satellite images are in the process of image processing to determine a flooding area by using the ERDAS imagine software. Firstly, water mask is generated by using the digitization technique. Thresholding technique is considered to segregating the water area and non-water area from satellite images during flooding time. Thresholding is a model maker in the ERDAS imagine tool. Then, the flood mapping is done by overlaying the inundated layer on the sub-district boundary map. Thereafter, each satellite image is classified flooding area by sub-district in each province. The area is in a unit of square kilometer and rai as Table 1.

Table 1 The example of flooded classification based on RADARSAT-2 on November 20, 2010

District/Sub-district	Flood area	
	Sq.km	Rai
Rasi Salai District	**62.59**	**39116.78**
Jig Sang Thong Sub-district	0.19	117.78
Dan Sub-district	4.53	2828.17
Bua Ung Sub-district	9.67	6042.60
Muang Kong Sub-district	4.07	2541.05
Muang Can Sub-district	0.63	396.43
Som Poy Sub-district	3.76	2352.35
Nong Ka Sub-district	14.60	9123.81
Nong Mhee Sub-district	0.05	29.69
Nong Ung Sub-district	25.10	15684.91
Sila Lad District	**11.58**	**7235.21**
Kung Sub-district	6.17	3853.07
Nong Bua Dong Sub-district	5.41	3382.14
Utumphon Phisai District	**1.84**	**1148.11**
Khok Lam Sub-district	0.10	65.07
Rung Rang Sub-district	1.73	1083.04

2. The positions of runoff stations are plot in a GIS map. The Digital Elevation Model or DEM data is concerned for the flow direction. Then, the effected flooding area from stream flow in each runoff station can be presented as following. The map of runoff station is concluded in Figure 1.

- M5: effects on Rasi Salai district and Yangchum district in Sisaket province,
- M9: effects on Muang Sisaket district in Sisaket province,
- M182: effects on Mueang Sisaket district and Kantrarom district in Sisaket province,
- M176: effects on Non Phon district and Kantrarom district in Sisaket province,
- M179A: effects on Khueang Nai district and Muang Samsib district in Ubon Ratchathani province,
- M179: effects on Muang Ubon Ratchathani district in Ubon Ratchathani province,
- M69: effects on Trakarn Phuet Phon district and Lao Sua Khok district in Ubon Ratchathani province,
- M7: effects on Mueang Ubon Ratchathani district, Warin Chamrap district, Sawangweerawong district, and Phibun Mangsahan district in Ubon Ratchathani province,
- M11B: effects on Phibun Mangsahan district in Ubon Ratchathani province,
- M170: effects on Det Udom district in Ubon Ratchathani province,
- E.20A: effects on Maha Chanchai district and Kho Wang district in Yasothon province,
- E.98: effects on Khueang Nai district in Ubon Ratchathani province and Kantrarom district Districts in Sisaket province.

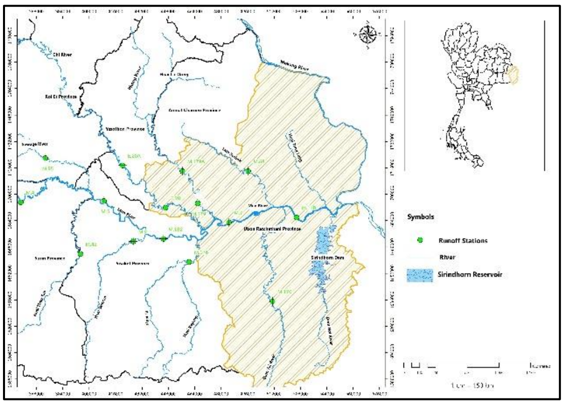


Figure 1 The runoff station in study area.

3. Both of water level and discharge are selected in the same day with 137 satellite images. Also, flooding area in each sub-district and district are matched to water level and discharge in each runoff station.

4. To consider the statistical relationship between two continuous variables, the Pearson's correlation coefficient is used in this study because this coefficient is the best method of measuring the association between variables of interest. It is based on the method of covariance, and it gives information about the magnitude of correlation. [25] The meaning of the Pearson's correlation coefficient shows in Table 2. [26] Then, the correlation between water level and flooding area is calculated by using the Pearson's correlation coefficient shows in Table 3. Also, the correlation between discharge and flooding area is evaluated by this coefficient shows in Table 4. The runoff station, where the Pearson's

correlation coefficient is more than moderate correlation, is selected to concern in next step.

Table 2 The meaning of the Pearson's correlation coefficient

correlation coefficient	Level of correlation
0.81-1.00	High
0.51-0.80	Moderate
0.21-0.50	Low
0.01-0.20	Very low.
0.00	No correlation

Table 3 The Pearson's correlation coefficient between water level and flood area

Runoff Stations	District	Water Level and Flood area	
		correlation coefficient	Level of correlation
M5	Rasi Salai	0.68	Moderate
M5	Yangchum	0.32	Low
M9	Muang Sisaket	0.68	Moderate
M182	Muang Sisaket	0.71	Moderate
M182	Kantrarom	0.59	Moderate
M176	Non Phon	0.21	Low
M176	Kantrarom	0.39	Low
M7	Mueang Ubon Ratchathani	0.71	Moderate
M7	Warin Chamrap	0.42	Low
M7	Sawangwerawong	0.43	Low
M7	Phibun Mangsahan	0.17	Low
M179	Mueang Ubon Ratchathani	0.58	Moderate
M179A	Khueang Nai	0.42	Low
M179A	Muang Samsib	0.17	Low
M69	Trakarn Phuet Phon	0.41	Low
M69	Lao Sua Khok	0.19	Low
M11B	Phibun Mangsahan	0.27	Low
M170	Det Udom	0.62	Moderate
E.20A	Kho Wang	0.54	Moderate
E.20A	Maha Chanchai	0.49	Low
E.98	Khueang Nai	0.55	Moderate
E.98	Kantrarom	0.46	Low

5. In addition, this study used F-Test values to consider the comparison of standard deviation (SD) or variance. F-Test is a statistical test based on null hypothesis. The results for calculation include F-Test and F-Critical value.

If F-Test < F-Critical means that the standard deviation of water level/discharge have a highly relationship with flooding area. [27] The F-Test results shown in Table 5 and Table 6. In Table 5, the F-Test values are normally less than F-Critical values that water level can be a mainly indicator for flood warning. On the other hand, in Table 6, the F-Test values are more than the F-Critical values that present the discharge can be a minor indicator for flood warning.

6. The relationship between water level/discharge and flooding area is evaluated in the runoff station where the Pearson's correlation coefficient is more than the moderate correlation. These are consisted of the station of M5, M9, M182, M7, M179, M170, E.20A, and E.98. Thereafter, all data is sorted in descending order.

The mean of water level and discharge are calculated to be a beginning flooding (Case I) and the maximum of water level and discharge are critical flooding (Case II). Finally, the big flooding in each area is concerned to be Case III as present in Table 7.

Table 4 The Pearson's correlation coefficient between discharge and flood area

Runoff Stations	District	Discharge and Flood area	
		correlation coefficient	Level of correlation
M5	**Rasi Salai**	**0.81**	**High**
M5	Yangchum	0.37	Low
M9	Muang Sisaket	0.52	Moderate
M182	Muang Sisaket	0.76	Moderate
M182	Kantrarom	0.54	Moderate
M176	Non Phon	0.21	Low
M176	Kantrarom	0.24	Low
M7	Mueang Ubon Ratchathani	0.76	Moderate
M7	Warin Chamrap	0.39	Low
M7	Sawangwerawong	0.46	Low
M7	Phibun Mangsahan	0.14	Low
M179	Mueang Ubon Ratchathani	0.65	Moderate
M179A	Khueang Nai	0.48	Low
M179A	Muang Samsib	0.38	Low
M69	Trakarn Phuet Phon	0.53	Moderate
M69	Lao Sua Khok	0.26	Low
M11B	Phibun Mangsahan	0.14	Low
M170	Det Udom	0.63	Moderate
E.20A	Kho Wang	0.73	Moderate
E.20A	Maha Chanchai	0.62	Moderate
E.98	Khueang Nai	0.78	Moderate
E.98	Kantrarom	0.44	Low

Table 5 The F-Test of water level and flood area

Runoff Stations	District	Water Level and Flood area	
		F-Test	F-Critical
M5	Rasi Salai	0.014	0.717
M5	Yangchum	0.256	0.717
M9	Muang Sisaket	0.028	0.721
M182	Muang Sisaket	0.025	0.721
M182	Kantrarom	0.036	0.728
M176	Non Phon	0.861	0.372
M176	Kantrarom	0.059	0.725
M7	Mueang Ubon	0.005	0.704
M7	Warin Chamrap	0.035	0.717
M7	Sawangwerawong	0.319	0.661
M7	Phibun Mangsahan	1.092	1.929
M179	Mueang Ubon Ratchathani	0.006	0.355
M179A	Khueang Nai	2.261	1.529
M179A	Muang Samsib	26.490	1.599
M69	Trakarn Phuet	0.108	0.511
M69	Lao Sua Khok	1.785	2.048
M11B	Phibun Mangsahan	0.931	0.488
M170	Det Udom	0.025	0.591
E.20A	Kho Wang	0.011	0.716
E.20A	Maha Chanchai	0.005	0.707
E.98	Khueang Nai	0.007	0.652
E.98	Kantrarom	0.089	0.649

Table 6 The F-Test of discharge and flood area

Runoff Stations	District	Discharge and Flood	
		F-Test	F-Critical
M5	Rasi Salai	660.283	1.396
M5	Yangchum	12520.853	1.394
M9	Muang Sisaket	89.581	1.389
M182	Muang Sisaket	2117.791	1.387
M182	Kantrarom	3091.999	1.374
M176	Non Phon	13948.16	2.687
M176	Kantrarom	169.624	1.378
M7	Mueang Ubon Ratchathani	2579.810	1.420
M7	Warin Chamrap	14044.91	1.394
M7	Sawangwerawong	170952.49	1.513
M7	Phibun Mangsahan	679934.4	1.929
M179	Mueang Ubon Ratchathani	89.214	2.818
M179A	Khueang Nai	56.778	1.529
M179A	Muang Samsib	594.344	1.599
M69	Trakarn Phuet Phon	567.176	1.955
M69	Lao Sua Khok	10337.452	2.048
M11B	Phibun Mangsahan	902404.6	2.124
M170	Det Udom	477.305	1.693
E.20A	Kho Wang	1366.800	1.389
E.20A	Maha Chanchai	685.136	1.406
E.98	Khueang Nai	402.345	1.534
E.98	Kantrarom	4895.130	1.540

4. RESULTS

The results of this study can be presented as following.

1. The runoff stations are analyzed the relationship between the water level (m MSL)/discharge (cms) and the flood area (sq.km) consisting of M5 (Rasi Salai), M9 (Mueang Sisaket), M182 (Mueang Si Saket, Kantrarom), M7 (Mueang Ubon Ratchathani, Warin Chamrap), M179 (Mueang Ubon Ratchathani), M170 (Det Udom), and E.20A (Kho Wang). Theses runoff station can present the water level and discharge for flood warning. Also, these stations should be developed to be the flood warning system.

2. Based on the Pearson's correlation coefficient, the moderate correlation between discharge and flooding area has a greater number of runoff station than that between the water level and flooding area. It can be concluded that the Pearson's correlation coefficient can be an indicator to concern the correlation of water level/discharge and flooding area. Moreover, the high correlation between discharge and flooding area is only in M5 (Rasi Salai). It means that flooding area can be strongly evaluated by stream flow data in M5 station.

Table 7 The maximum, mean, and minimum for water level, discharge, and flooding area.

Stations	District	Water level (m MSL)			Discharge (cms)		
		Case I	Case II	Case III	Case I	Case II	Case III
M5	Rasi Salai	119.45	120.25	121.49	1375.47	1678.21	3066.00
M9	Muang Sisaket	119.35	120.53	122.09	221.14	309.21	633.40
M182	Muang Sisaket and Kantrarom	116.54	117.37	119.39	1386.65	1485.01	3026.50
M7	Muang Ubon Ratchathani and Warin Chamrap	112.00	113.54	115.96	2300.00	3357.01	5134.00
M179	Muang Ubon Ratchathani	113.00	113.97	114.59	301.90	425.10	513.50
M170	Det Udom	131.42	132.29	133.29	303.61	543.47	1312.50
E.20A	Kho Wang	121.94	122.45	123.97	1140.53	1407.62	2662.50
E.98	Khueang Nai	116.41	117.49	117.94	820.57	1310.91	1714.00

3. For the flood warning indicators at Sisaket province as Table 7, the water level and discharge at M5, M9, and M182 should be consider because there is a higher relationship between water level/discharge and flooding area than others runoff station in Sisaket province.

- M5: the water level of 119.45 m MSL and discharge of 1375.47 cms will start for flooding in Rasi Salai district. The water level and discharge for critical flooding are 120.25 m MSL and 1678.21 cms, respectively.

- M9: the water level of 119.35 m MSL and discharge of 221.14 cms will start for flooding Muang Sisaket district. The water level and discharge for critical flooding are 120.53 m MSL and 309.21 cms, respectively.

- M182: the water level of 116.54 m MSL and discharge of 1386.65 cms will start for flooding in Muang Sisaket district and Kantrarom district. The water level and discharge for critical flooding are 117.37 m MSL and 1485.01 cms, respectively.

In Sisaket province, it is importance to increase river capacity in M9 because a river capacity at M9 is lower than that of M5 and M182 where are an upstream and downstream, respectively.

4. Ubon Ratchathani province is a downstream of the Mun river, so it receives water from Sisaket province and the Chi River. A big flood was occurred in many times. The flood warning indicators at Ubon Ratchathani province, as Table 7, can be defined from M7, M179, M170, E.20A, and E.98 stations because there is a higher relationship between water level/discharge and flooding area than others runoff station in this province.

M7: the water level of 112.00 m MSL and discharge of 2300.00 cms will start for flooding in Muang Ubon Ratchathani and Warin Chamrap district. The water level and discharge for critical flooding are 113.54 m MSL and 3357.01 cms, respectively.

M179: the water level of 113.00 m MSL and discharge of 301.90 cms will start for flooding in Muang Ubon Ratchathani district. The water level and discharge for critical flooding are 113.97 m MSL and 425.10 cms, respectively.

M170: the water level of 131.42 m MSL and discharge of 303.61 cms will start for flooding in Det Udom district. The water level and discharge for critical flooding are 132.29 m MSL and 543.47cms, respectively.

E.20A: the water level of 121.94 m MSL and discharge of 1140.53 cms will start for flooding in Kho Wang district. The water level and discharge for critical flooding are 122.45 m MSL and 1407.62 cms, respectively.

E.98: the water level of 116.41 m MSL and discharge of 820.57 cms will start for flooding in Khueang Nai district. The water level and discharge for critical flooding are 117.49 m MSL and 1310.91 cms, respectively.

5. CONCLUSION

1. The flood warning indicators is shown in Figure 2. This figure presents a minimum, mean, and maximum values of water level and discharge for flood warning. The minimum values are the beginning of flooding so people in an area should prepare themselves to move up. The water along Mun river should gradually drainage to downstream. The mean values of water level and discharge present a serious flood situation, it is important to move people out and to quicky drainage water out. Finally, the maximum values of water level and discharge are a very serious of flooding or a big flooding.

2. Since the Muang Ubon Ratchathani district have water barrier flap along the Mun river, flood is occurred after flooding occurred in the Warin Chamrap district. Although the side flow from M179 is only 10.00-371.80 cms, it is importance to watch an excess stream flow from this station. Moreover, an excess flow from E.20A and E.98 is very significant to concern because there are a lot of water from these stations or from the Chi River. The stream flow from M69 is a side flow to the downstream of the Muang Ubon Ratchathani district or M7 station. It is necessary to concern water release from M69 when there is flooding in the Muang Ubon Ratchathani district. If there is a low water in downstream, there is a convenient flow in upstream

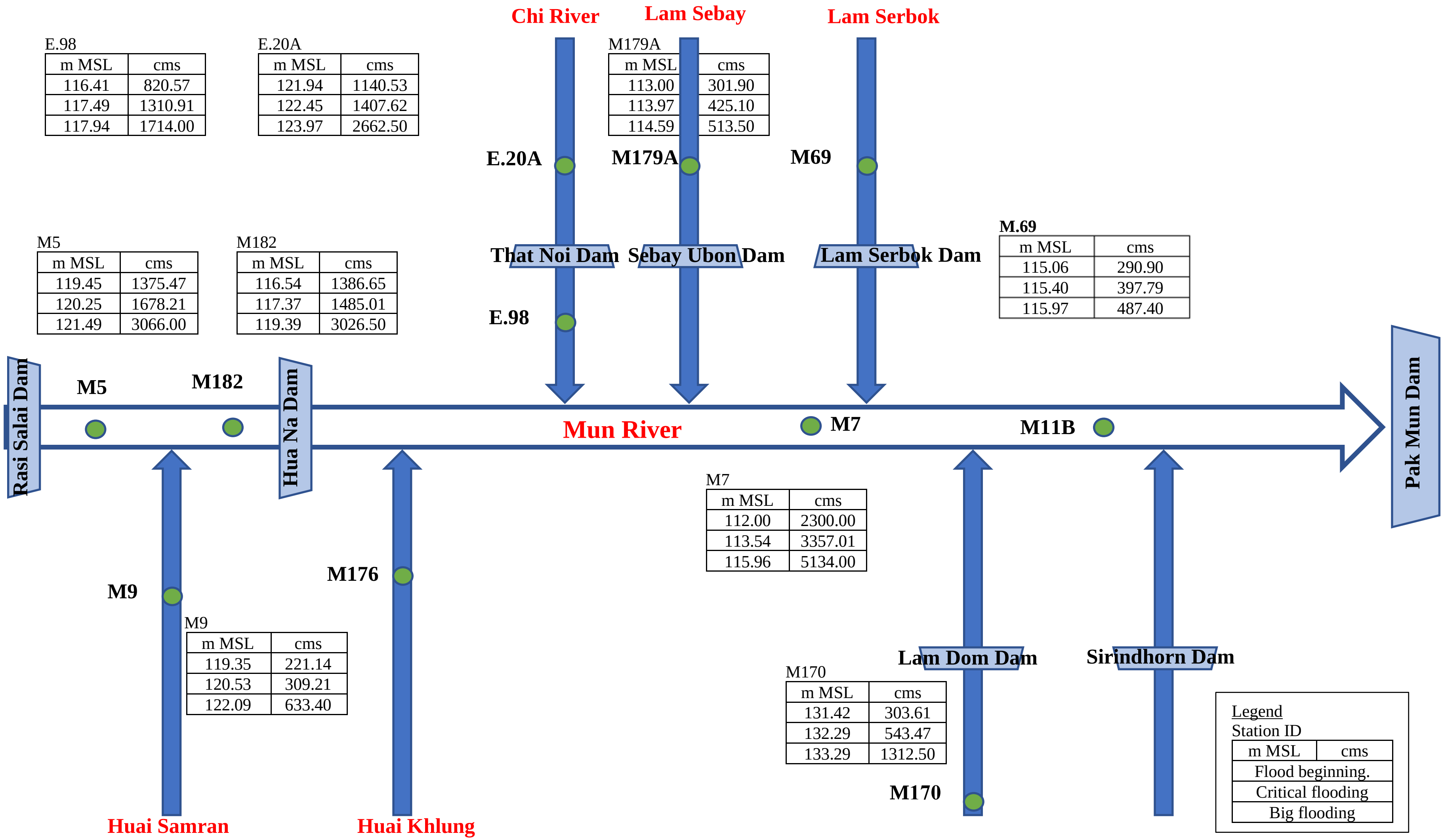
3. The flood warning indicators has both of advantage and disadvantage when is compared to the traditional flood warning as Table 8.

Table 8 The comparison between traditional flood warning method and flood warning indicators

Traditional flood warning method	**Flood warning indicators**
Mathematic model, weather data, stream flow data	ERDAS imagine software, satellite image, and stream flow data
Construct the telemetry system that is expansive	Original tools at runoff station
Complex methodology	Basic methodology
High-cost operation and management	Low-cost operation and management
Real-time warning system	Static warning
Specific area	Specific area
Rainfall and runoff are mainly input data.	Runoff is mainly input data.
Requires a high level of experts	Requires the experts
New data is collected all time.	New data is not collected.

6. RECOMMENDATION

Flood warning in both of Sisaket province and Ubon Ratchathani province is very importance. The flood warning indicator from this study is an initial flood warning system because it is analyzed from a huge data of stream flow and satellite images. Also, the result can specific the runoff stations where should construct a telemetry tool. However, this study did not think about the effect of rainfall on the flooding which is an importance parameter. Moreover, to complete the study of flood warning, the mathematical modelling should be concerned to include the effect of rainfall, dynamic stream flow, and gate operation. The diversity scenario, such as flood solution and flood operation, should run in the mathematical modelling.



E.98

m MSL	cms
116.41	820.57
117.49	1310.91
117.94	1714.00

E.20A

m MSL	cms
121.94	1140.53
122.45	1407.62
123.97	2662.50

M179A

m MSL	cms
113.00	301.90
113.97	425.10
114.59	513.50

M5

m MSL	cms
119.45	1375.47
120.25	1678.21
121.49	3066.00

M182

m MSL	cms
116.54	1386.65
117.37	1485.01
119.39	3026.50

M.69

m MSL	cms
115.06	290.90
115.40	397.79
115.97	487.40

M7

m MSL	cms
112.00	2300.00
113.54	3357.01
115.96	5134.00

M9

m MSL	cms
119.35	221.14
120.53	309.21
122.09	633.40

M170

m MSL	cms
131.42	303.61
132.29	543.47
133.29	1312.50

Figure 2 The stream flow for flood warning.

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Hydroinformatics

ASSESSMENT OF WEAP MODEL IN SIMULATING RAINFALL-RUNOFF RELATION IN THE PING AND WANG RIVER BASINS, THAILAND

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ABSTRACT

This study aimed at developing the physically–based rainfall–runoff model using the Water Evaluation and Planning system (WEAP) with the simplified coefficient method. The Ping and Wang River Basins in the northern region of Thailand were selected as study area to explain the hydrologic dynamics and responses of the implemented watershed system through rainfall–runoff relation. The monthly hydro–meteorological data during 2000–2020 was used as dataset for hydrological modelling by WEAP. To reflect the lumped hydrologic response, the study area in Ping and Wang River Basins were subdivided into 3 sub–basins; (1) Sub–Basin 1 (Upper Ping Basin), (2) Sub–Basin 2 (Lower Ping Basin), and (3) Sub–Basin 3 (Wang Basin). In addition, the land area was fractionally classified into 16 land use classes to identify the relevant inputs such as crop coefficient, areal rainfall, and reference evapotranspiration. Key model parameters; runoff coefficient, infiltration coefficient, and percent of effective rainfall, were estimated and adjusted manually to improve the model performance statistics. The model calibration and validation were implemented through comparison between monthly observed and simulated streamflow measured at 3 gauging stations; P.12C, P.17, W.4A on the Ping and Wang Rivers as well as the monthly inflow of Bhumibol Dam. The long–term simulation results showed that WEAP model could provide the reasonably good agreement of R^2 of 0.75–0.81 at all gauging stations except P.12C station where the hydrologic response has been strongly affected by the influence of regulated dam release. Based on the overall model performance statistics, predominant capability of WEAP model to simulate behavior of hydrologic responses was found particularly at the outlet of sub–basin (P.17 and W.4A gauging stations) and outflow point (reservoir inflow of BB Dam) where the impact of regulated flow on the model performance has been diminished.

Keywords: Ping River Basin, Wang River Basin, WEAP model, Rainfall–Runoff simulation

1. INTRODUCTION

The changing global climate driven by human–induced activities has drastically impacted on the world's water systems through the frequent occurrences of natural disasters. In Thailand, the impact of climate change has become the serious problems. It has led to the complexity of water resources management issues especially for the dam operation since the 2011 major flood occurred in the Northern and Central regions of Thailand. The significant changes of the regional scale shifts in the rainfall patterns have resulted in the incapability to potentially store water in the major reservoirs such as Bhumibol and Sirikit Dams in the northern region of Thailand. In the recent years, it is observable that the tendency of tropical storms occurring all year round regularly in this region is likely short in duration and sudden delay in the commencement or termination of rain particularly in wet season. Therefore, the considerable attention to unbalancing of the spatio–temporal distribution of water availability and water demands have been paid by the key operational offices to reduce the economic losses caused by flooding and droughts.

Understanding the hydrologic behaviors and watershed responses altered by the influence of climate changes and anthropologic factors has played important role in coping with the hydrologic uncertainty and water supply–demand imbalance. Model–based assessment has been widely used to simulate both natural hydrological processes, land development activities, human–induced effects, and management strategies on water resources [1]. The relation of rainfall and runoff processes, low flow and flood peaks behaviors or the hydrologic properties can be well characterized by the physically–based hydrologic models [2]. The various types of the physically–based hydrologic models have been adopted to enhance understanding of the hydrologic processes and watershed responses [3]. The hydrological modelling practices through lumped and distributed parameter models such as

SWAT, WEAP, HEC–HMS, MIKE HYDRO Basin and others have been made in many parts of the world to explore the potential interactions among involved factors [4].

WEAP (water evaluation and planning) model was developed by the Stockholm Environment Institute (SEI) in 1988 [5]. It is a sort of lumped–parameter hydrologic representation creating the simulations of the natural rainfall–runoff processes and the management of implemented water system [1]. It is well known that WEAP model can be successfully used for climate change adaptation studies and a wide range of operational manageability of water resources [6].

In this study, the WEAP hydrologic model was developed for the Ping and Wang River Basins by aiming to assess the model efficiency in simulating the rainfall–runoff relation and to explain the hydrologic dynamics and responses of the implemented watershed system over long term periods in this region.

2. METHODOLOGY

2.1 Study Area

Ping and Wang River Basins are located in the northern region of Thailand with the total drainage area of 45,499 km^2 as shown in Fig.1. Ping and Wang River Basins have been considered as major sources of water to help support in supplying irrigation water for the Lower Ping and Chao Phraya Irrigation Schemes as well as for non–irrigation water uses downstream of the Bhumibol Dam. Ping River Basin covers 6 provinces in Thailand; Chiang Mai, Lamphun, Tak, Kamphaeng Phet, Nakhon Sawan, and Mae Hong Son. Approximately 67.32% of the land cover in the Ping River Basin is forest and agricultural land area is 25.17%. The urban and built–up land and miscellaneous land are 3.71% and 2.08%, respectively. The remaining portion of 1.71% is surface water body. The average monthly rainfall over the entire basin are approximately 163.99 mm/month in wet season (May–Oct) and 22.23 mm/month in dry season (Nov–Apr) showing high temporal variability of the rainfall amount [7].

Wang River Basin is situated close to Ping River Basin covering 4 provinces; Chiang Rai, Lampang, Tak, and Phrae in the North. Wang River is one of the principal tributaries of the Chao Phraya River flowing southwards to join the Ping River in Tak Province before discharging into the Chao Phraya River and the Gulf of Thailand. Most of the land area in the Wang River Basin is forest accounting for 73.09% of the entire basin. The percentage share of agricultural and urban and built–up land areas over the entire basin are 18.29% and 3.98%, respectively. The remaining 2.08% and 1.17% are miscellaneous land and water body. It is recorded that average monthly rainfall in wet and dry seasons in Wang River Basin are 160.21 mm/month and 22.85 mm/month, respectively which are not much deviated from rainfall amount in Ping River Basin [7]. In other words, approximately 88% of the yearly rainfall falls during wet season and 12% exists during dry season in the Ping and Wang River Basins.

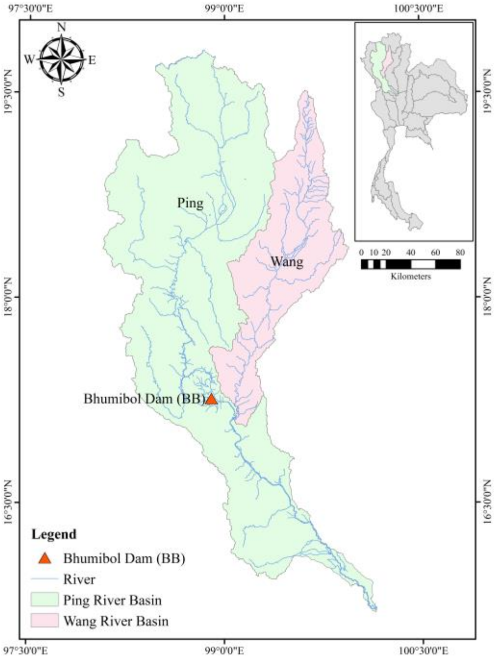

Figure 1 Location of the Ping and Wang River Basins in the northern region in Thailand

2.2 Hydrological Model Development

2.2.1 Data Collection

Data collection procedures was firstly conducted in this study to gather the input data required for the formulation of WEAP model in the Ping and Wang River Basins. The long–term hydro–meteorological data during 2000–2020 was preliminarily investigated and used. In addition, WEAP requires catchment and land use data, climate data, water demand site data, as well as reservoir data to accomplish the modelling processes of rainfall–runoff simulation in the implemented watershed system. This primary data was collected mainly from the Royal Irrigation Department (RID), Electricity Generating Authority of Thailand (EGAT), Thai Meteorological Department (TMD), Land Development Department (LDD), and other secondary sources as summarized in Table 1.

Table 1 Data required for this study

No.	Data Type	Data Source
1	Reservoir Data	EGAT
2	Hydro–Meteorological Data	
	• Rainfall	RID and TMD
	• Runoff	RID

	• Climate Data	TMD
3	Land use Data	LDD
4	Water Demand Data	
	• Agricultural Water Demand	Secondary Source [8]
	• Non–Agricultural Water Demand	Secondary Source [8]

2.2.2 Development of Rainfall–Runoff Model by WEAP Model

(1) Hydrological Method Selected

The WEAP hydrologic model was developed to simulate the watershed processes in term of rainfall–runoff relation in the Ping and Wang River Basins using the simplified coefficient method. The modelling processes were carried out according to process flow diagram as shown in Fig.2. The rainfall–runoff simulation by the simplified coefficient method in WEAP principally determines evapotranspiration for irrigated and rainfed crops using crop coefficients (Kc). The remainder of rainfall amount which is not consumed by crop evapotranspiration, is simulated as runoff to a river. In other words, it can be proportioned among runoff to a river and flow to groundwater via runoff/infiltration links [5].

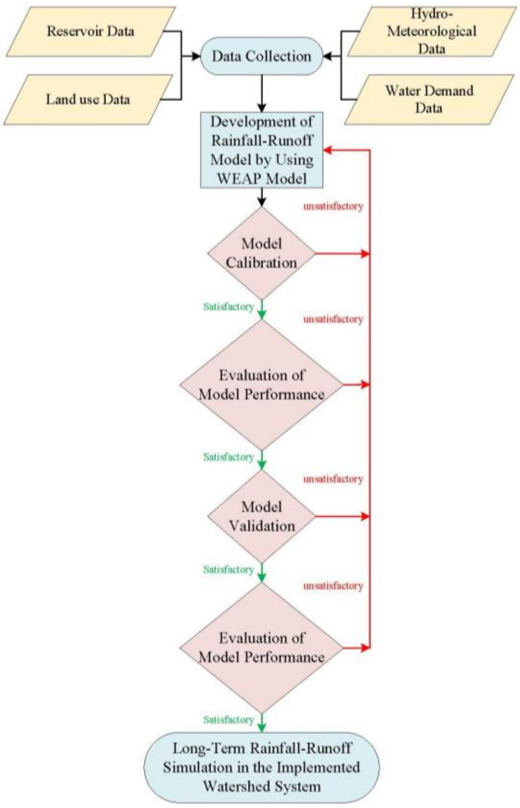

Figure 2 Process flow diagram of WEAP model development in the study area

(2) Basin Division

To reflect the lumped hydrologic response in WEAP model, the study area in Ping and Wang River Basins were subdivided into 3 sub–basins; (1) Sub–Basin 1 (Upper Ping Basin, SB1), (2) Sub–Basin 2 (Lower Ping Basin, SB2), and (3) Sub–Basin 3 (Wang Basin, SB3) as shown in Fig.3. In addition, the land area was fractionally classified into 16 land use classes: paddy field (A1), field crop (A2), perennial crop (A3), orchard (A4), horticulture (A5), shifting cultivation (A6), pasture and farmhouse (A7), aquatic plant (A8), aqua–cultural land (A9), evergreen forest (F1), deciduous forest (F2), rangeland (M1), marsh and swamp (M2), city town (U1), village (U2), and water body (W). The percentage share of land use classes was presented as a percentage of total area as summarized in Table 2

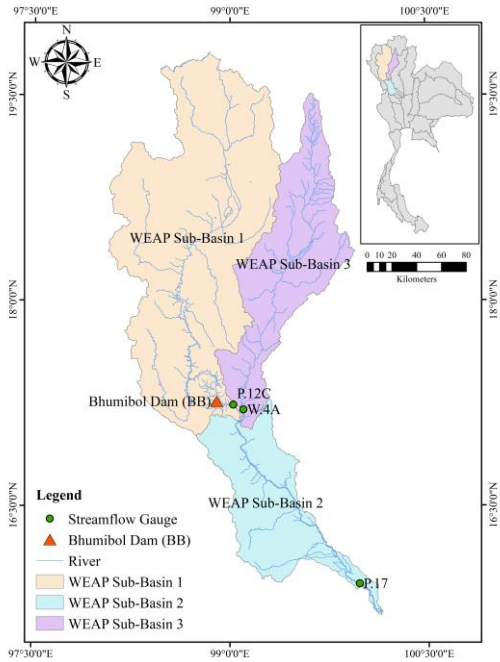

Figure 3 Basin division and key streamflow gauges used for model calibration and validation

Table 2 Land use data classified in each sub–basin

Class	Sub–Basin 1		Sub–Basin 2		Sub–Basin 3	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
A1	1,082.28	4.13	1,162.75	14.14	935.36	8.67
A2	1,149.46	4.38	2,174.56	26.44	924.67	8.57
A3	117.12	0.45	222.00	2.70	534.93	4.96
A4	1,909.64	7.28	152.95	1.86	144.22	1.34
A5	137.16	0.52	17.35	0.21	4.64	0.04
A6	1,084.90	4.14	74.41	0.90	39.69	0.37
A7	32.30	0.12	92.63	1.13	16.38	0.15
A8	0.19	0.00	0.01	0.00	0.03	0.00
A9	4.72	0.02	4.24	0.05	2.08	0.02
F1	3,985.08	15.19	364.16	4.43	862.32	7.99
F2	14,808.52	56.45	3,243.09	39.43	6,427.24	59.58
M1	376.66	1.44	70.59	0.86	112.00	1.04

M2	96.65	0.37	66.90	0.81	130.81	1.21
U1	315.58	1.20	135.79	1.65	162.17	1.50
U2	703.00	2.68	268.47	3.26	320.48	2.97
W	431.73	1.65	175.59	2.13	170.58	1.58
Total	26,235	100	8,225	100	10,788	100

Remark: A1= paddy field, A2 = field crop, A3 = perennial crop, A4 = orchard, A5 = horticulture, A6 = shifting cultivation, A7 = pasture and farmhouse, A8 = aquatic plant, A9 = aqua–cultural land, F1 = evergreen forest, F2 = deciduous forest, M1 = rangeland, M2 = marsh and swamp, U1 = city town, U2 = village, and W = water body

(3) Data Entry

The specific point rainfall gathered from 25 rainfall stations in the Ping and Wang River Basins and adjacent area as can be seen in Fig.4, was used and transformed into areal rainfall by Thiessen polygon technique in order to identify the representation of monthly rainfall input of each sub–basin. The monthly reference evapotranspiration (ETo) was estimated using evaporation pan method which requires the evaporation loss data from field observation as shown the list of climate stations in Table 3 and Fig.5. Accordingly, the average monthly evaporation losses for each sub–basin were estimated for the estimation of reference evapotranspiration by multiplying with the pan coefficient (Kp).

Table 3 Rainfall & climate stations considered in this study

Sub–Basin	Rainfall Station	Climate Station
SB1	70391	48326: Mae Jo Agromet.
	70731	
	300201	48327: Chiang Mai
	300202	
	303301	48329: Lamphun
	310201	48377: BB Dam
	327501	
	328301	
	329201	
	376203	
	630181	
SB2	120081	48376: Tak
	120121	48380:Kamphaeng Phet
	120161	
	160221	
	260271	
	260311	
	376201	
	376203	
	376301	
	376401	
	380201	
	400201	
	630181	
SB3	70391	48328: Lampang
	160151	48324: Thoen
	160221	48334: Lampang Agromet.
	303301	
	310201	
	328201	
	328301	
	329201	
	376201	
	376203	
	400111	
	400151	

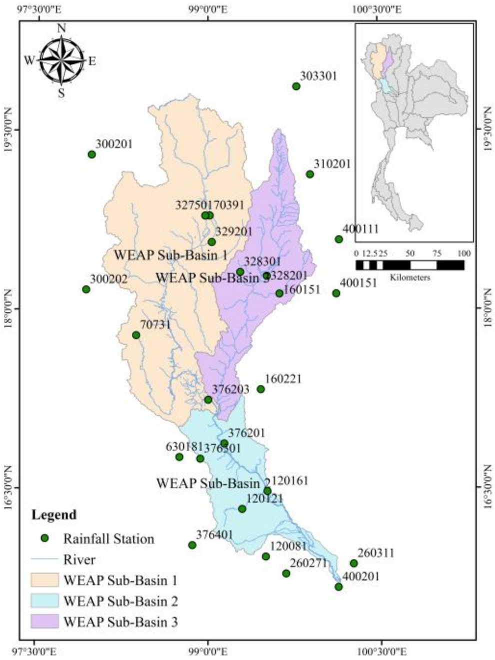

Figure 4 Location of rainfall stations

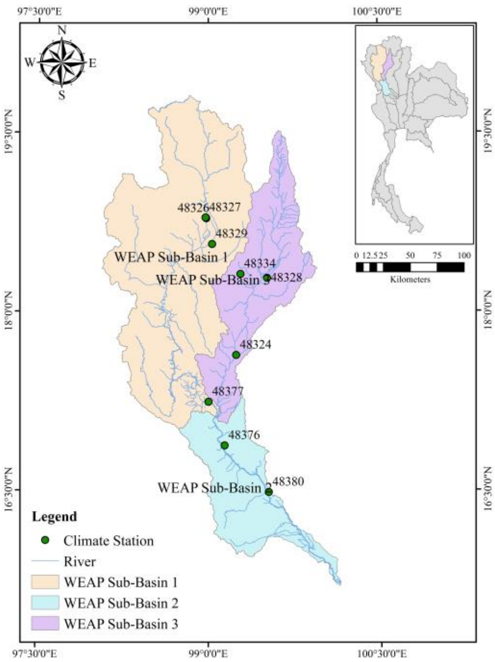

Figure 5 Location of climate stations

Table 4 Summary of average monthly rainfall and ETo identified in each sub–basin

Month	SB1		SB2		SB3	
	Rain* (mm)	ETo (mm)	Rain* (mm)	ETo (mm)	Rain* (mm)	ETo (mm)
Jan	280.4	100.9	225.8	106.1	337.1	102.5
Feb	98.1	122.2	206.3	128.5	131.4	126.4
Mar	433.7	162.7	705.0	171.5	608.5	170.5
Apr	1,176.9	179.8	1,223.3	187.4	1,372.8	181.5
May	3,599.3	158.6	3,524.7	164.3	3,973.4	157.2
Jun	2,801.0	138.4	2,978.1	129.4	2,376.4	131.8
Jul	2,932.4	125.2	2,865.8	121.9	2,681.3	119.6
Aug	3,912.7	121.5	3,381.7	118.5	3,924.0	115.2
Sep	4,153.9	107.6	5,232.7	110.5	4,249.0	112.1
Oct	2,658.8	111.5	3,904.3	98.9	2,674.4	102.7
Nov	759.9	97.4	652.7	92.2	570.4	93.4
Dec	216.2	95.7	144.6	94.9	207.0	91.5

Remark: * Areal rainfall

The values of crop coefficient (Kc) for each land use class were determined to estimate the crop evapotranspiration (ETc) as summarized in Table 5.

Table 5 Crop coefficient values identified for each land use class

Land Use Class	Kc Value
A1	1.30
A2	1.01
A3	1.10
A4	1.20
A5	1.13
A6	0.88
A7	0.49
A8	1.00
A9	0.90
F1	0.35
F2	0.38
M1	0.90
M2	0.90
U1	0.77
U2	0.80
W	1.00

Source: [6]

Interactions between surface water (Sub_Basin_1, Sub_Basin_2, Sub_Basin_3) and groundwater (GW_SB_1, GW_SB2, GW_SB3) in each sub–basin were specified and hydraulically connected in WEAP model. For the demand data, two branches of demand site for agricultural water use (WD_LPWDZ) and non–agricultural water use (WS_LPWDS) were identified downstream of Bhumibol Dam to supply irrigation water to the Lower Ping Irrigation Scheme and non–irrigation water use to the downstream region as shown in Fig.6. The demand priority was then set up on the transmission link equally for both irrigation water and non–irrigation water uses to avoid water scarcity for all demand sectors.

The model calibration was conducted by adjusting key parameters of rainfall–runoff processes namely runoff coefficient, infiltration coefficient, and effective rainfall to match the real behavior of hydrologic system. The model accuracy was verified by the validation procedure using the past data. In this study, the model calibration and validation were implemented through comparison between monthly observed and simulated streamflow measured at 3 gauging stations; P.12C, P.17, W.4A on the Ping and Wang Rivers as well as the monthly inflow of Bhumibol Dam during 2000–2020.

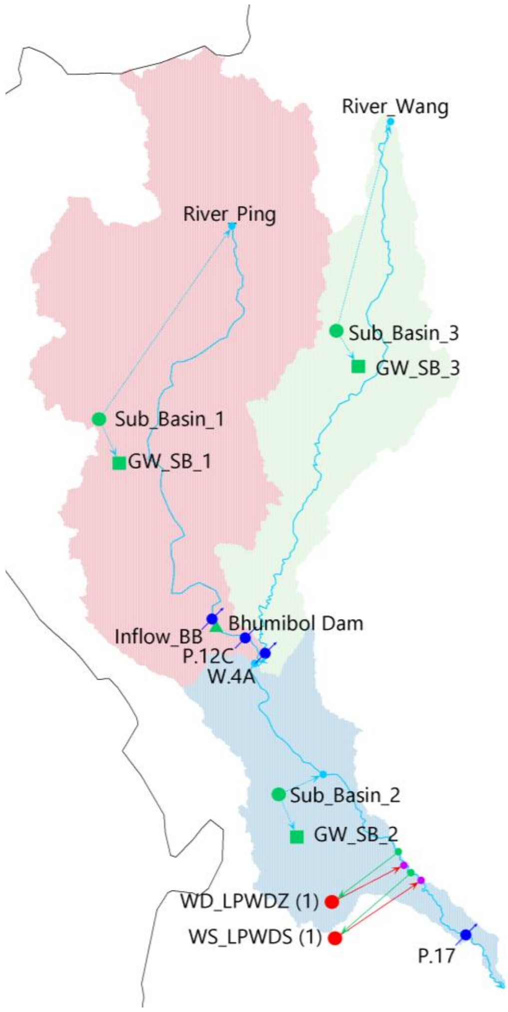

Figure 6 Development of WEAP model for rainfall–runoff simulation in the Ping and Wang River Basin

2.3 Assessment of WEAP Model Performance

To assess the WEAP model performance for rainfall–runoff simulation, statistical indices namely; Percent Bias (PBIAS), Nash–Sutcliffe Efficiency (NSE), Index of Agreement (d), RMSE–Observations Standard Deviation Ratio (RSR), and Volumetric Efficiency (VE) were evaluated as described below;

2.3.1 Percent Bias (PBIAS)

Percent bias (PBIAS) measures the average tendency of the simulated values to be larger or smaller than their observed ones. The optimal value of PBIAS is 0. The small values of PBIAS indicate high accuracy of the model simulation. However, the positive values of PBIAS reflect overestimation bias, whereas negative values express underestimation bias of the model simulation. The model performance is in general satisfactory if PBAIS is ± 25% [6].

$$PBIAS=100\left(\frac{\sum_{i=1}^{N}(O_i-S_i)}{\sum_{i=1}^{N}O_i}\right) \qquad (1)$$

2.3.2 Nash–Sutcliffe Efficiency (NSE)

The Nash–Sutcliffe Efficiency (NSE) is a normalized statistic to measure the relative magnitude of the residual variance compared to the measured data variance. It is absolutely similar to the coefficient of determination (R^2).

$$NSE=1-\left(\frac{\sum_{i=1}^{N}(O_i-S_i)^2}{\sum_{i=1}^{N}(O_i-\bar{O})^2}\right) \qquad (2)$$

For monthly hydrographical data, NSE values range between −∞ and 1.0. NSE = 1.0 is the perfect fit, NSE > 0.75 is a very good fit, NSE = 0.65 to 0.75 is a good fit, NSE = 0.5 to 0.65 is a satisfactory fit and NSE < 0.5 is an unsatisfactory fit [9].

2.3.3 Index of Agreement (d)

Index of Agreement (d) is a standard measure to explain the degree of model error. Values of agreement index varies between 0–1. Higher values indicate better agreement between the model outputs and observations.

$$d=1-\left(\frac{\sum_{i=1}^{N}(O_i-S_i)^2}{\sum_{i=1}^{N}(|S_i-\bar{O}|+|O_i-\bar{O}|)^2}\right) \qquad (3)$$

2.3.4 Ratio of RMSE to the Standard Deviation of the Observations (RSR)

RMSE–Observations Standard Deviation Ratio (RSR) is the standardized form of RMSE. Ratio of RMSE to the standard deviation of the observations is expressed in the following equation. The model performance is satisfactory when RSR ≤ 0.70. RSR > 0.70 is rated as unsatisfactory for monthly data [9].

$$RSR=\frac{RMSE}{STDEV_{obs}}=\frac{\sqrt{\sum_{i=1}^{N}(O_i-S_i)^2}}{\sqrt{\sum_{i=1}^{N}(O_i-\bar{O})^2}} \qquad (4)$$

3.4.5 Volumetric Efficiency (VE)

Volumetric Efficiency (VE) is the statistical measure to describe the model efficiency in term of volumetric residual between the model outputs and observations. The values of VE vary between 0–1. The perfect agreement between observed and simulated values is found when VE is equal to 1.

$$VE=1-\frac{\sum_{i=1}^{N}|S_i-O_i|}{\sum_{i=1}^{N}O_i} \qquad (5)$$

where O_i is observed values at time i, S_i is modeled/simulated values at time i, N is the number of observed values, $\bar{O}$ is the average value of the observed values, and $\bar{S}$ is the average value of the modeled values.

3. RESULTS AND DISCUSSIONS

3.1 Model Calibration and Validation

In this study, model calibration was conducted using the dataset from 2000–2015 by aiming at receiving the suitable model parameters reasonably to represent the hydrologic behavior of the Ping and Wang River Basins. Table 6 shows the estimated values of model parameters in each sub-basin including runoff coefficient, infiltration coefficient, and percent of effective rainfall. Estimating model parameters in WEAP was made by manual adjustment to minimize the difference between the observed and simulated flows at key gauging stations; P.12C, P.17, W.4A and reservoir inflow of Bhumibol Dam. Validation procedure was also conducted using dataset during 2016–2020 to assess the model validity for the simulation of hydrologic response.

It is found that the estimated values of runoff coefficient for 3 sub–basins varies from 0.10–0.25 describing surface runoff potential in the Ping and Wang Basins where the large portion of total land area is vastly forestland and agricultural areas. The infiltration coefficient in WEAP model is inversely correlated with the runoff coefficient to describe capability of water penetrating into soils. It is exhibited that the infiltration coefficient ranges from 0.75–0.90 for these 3 sub–basins. In addition, the effective rainfall explaining the net amount of rainfall potentially consumed by crops, varies greatly subject to the specific land use classes and hydro–geological conditions for each sub–basins as can be seen in Table 6.

Table 6 Estimation of model parameters by the simplified rainfall–runoff method in WEAP

WEAP Parameters		Sub–Basin 1	Sub–Basin 2	Sub–Basin 3
Runoff Coefficient		0.25	0.10	0.18
Infiltration Coefficient		0.75	0.90	0.82
Effective Rainfall (%)	A1	85	99	64
	A2	42	16	67
	A3	92	24	88
	A4	22	84	34
	A5	43	46	3
	A6	92	91	88

	A7	29	91	12
	A8	42	100	88
	A9	41	68	96
	F1	63	79	97
	F2	69	17	61
	M1	46	55	28
	M2	4	65	90
	U1	80	63	97
	U2	36	69	92
	W	100	100	100

3.2 Assessment of Model Performance

The efficiency of model performance was considerably investigated using the statistics assessed from the simulated outputs performed by WEAP model and observed flow data at key gauging stations; P.12C, P.17, W.4A and reservoir inflow of Bhumibol Dam. The model performance statistics for rainfall–runoff simulation during calibration and validation periods and long–term simulation periods are presented in form of PBIAS, NSE, R^2, RSR, d, and VE as summarized in Table 4.

It exhibits the similar pattern of the simulated and observed monthly flows at P.12C, P.17, W.4A stations and reservoir inflow of Bhumibol Dam when long–term simulation during 2000–2020 is implemented as qualitatively displayed in Fig.7–Fig.10.

For the calibration period during 2000–2015, the model performance shows good agreement of R^2 index of 0.80 and 0.76 at P.17 and W.4A gauging stations. Moreover, the model performance could be achieved in simulating the monthly reservoir inflow of BB Dam with R^2 of 0.82. Moreover, a normalized statistic measured in form of NSE value shows good fit of 0.72–0.80 at P.17 and W.4A gauging stations, and BB inflow.

However, the model performances are slightly decreased when the model validation during 2016–2020 is performed for P.17 and W.4A stations and BB inflow with R^2 of 0.63–0.75 and NSE of 0.44–0.65. For the long–term simulation during 2000–2020, it provides the reasonably good agreement of R^2 of 0.72–0.81 and NSE of 0.71–0.78 at all gauging stations except P.12C station. It is investigated that the streamflow data at P.12C station located downstream of BB Dam, is strongly associated with the regulated dam release. Therefore, further study in setting up related parameters for reservoir operation of BB Dam corresponding to the current operational practices should be reconsidered to improve the model performance particularly at P.12C station.

Table 7 Summary of model performance statistics for rainfall–runoff simulation in the Ping and Wang River Basins

Statistics	Streamflow Gauging Stations			
	BB Inflow	P.12C	P.17	W.4A
Calibration Periods (2000–2015)				
PBIAS	16.67	18.44	12.70	28.47
NSE	0.80	-0.27	0.77	0.72
R^2	0.82	0.29	0.80	0.76
RSR	0.45	1.13	0.48	0.53
d	0.80	-0.26	0.77	0.73
VE	0.62	0.63	0.77	0.47
Validation Periods (2016–2020)				
PBIAS	35.10	34.39	57.77	28.27
NSE	0.65	-0.53	0.44	0.59
R^2	0.74	0.14	0.75	0.63
RSR	0.59	1.24	0.75	0.64
d	0.65	-0.53	0.44	0.60
VE	0.51	0.66	0.42	0.43
Long–Term Simulation (2000–2020)				
PBIAS	20.05	20.70	18.24	28.44
NSE	0.78	-0.30	0.73	0.71
R^2	0.81	0.29	0.79	0.75
RSR	0.47	1.14	0.52	0.54
d	0.78	-0.29	0.73	0.71
VE	0.60	0.64	0.73	0.46

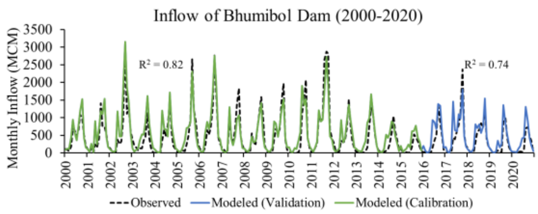

Figure 7 Comparison of simulated and observed monthly inflows of BB Dam

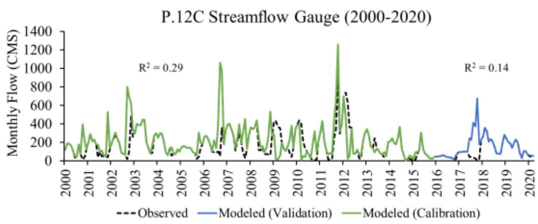

Figure 8 Comparison of simulated and observed monthly flows at P.12C station

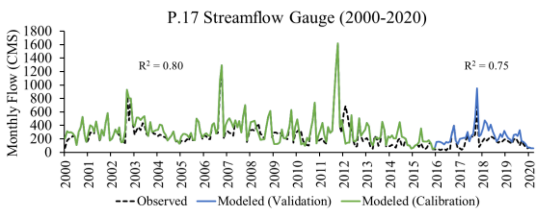

Figure 9 Comparison of simulated and observed monthly flows at P.17 station

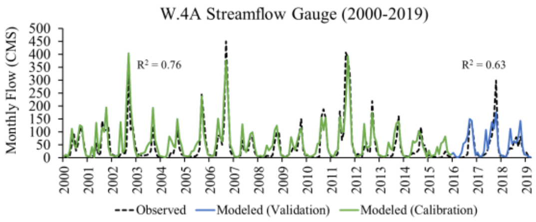

Figure 10 Comparison of simulated and observed monthly flows at W.4A station

4. CONCLUSIONS

WEAP hydrologic model was developed for the Ping and Wang River Basins in the northern region of Thailand by aiming to assess the model efficiency in simulating the rainfall–runoff relation to explain the hydrologic dynamics and responses of the implemented watershed system over long–term periods. The long–term simulation results showed that WEAP model could provide the reasonably good agreement of R^2 of 0.75–0.81 at key gauging stations; P.17, W.4A and reservoir inflow of Bhumibol Dam except P.12C station where the hydrologic response has been strongly affected by the influence of regulated dam release. Based on the overall model performance statistics, predominant capability of WEAP model to simulate behavior of hydrologic responses was found particularly at the outlet of sub–basin (P.17 and W.4A gauging stations) and outflow point (reservoir inflow of BB Dam) where the impact of regulated flow on the model performance has been diminished.

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