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ORIGINAL ARTICLE

Fuzzy rule–based control of multireservoir operation system for flood and drought mitigation in the Upper Mun River Basin

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Abstract

Strategic reservoir operation, a primary water management measures, plays a significant role in mitigating floods and droughts. Since the reservoir operation involves making complicated decisions on uncertain hydrological variables driven by climate variability, therefore, constructive tool for decision making like fuzzy logic is essential to optimize reservoir management and ensure water security. This study demonstrated fuzzy logic application to multiple reservoir operation in tropical region like Thailand. A Fuzzy Rule–Based Model (FRBM) exploiting FL approach was developed to control the upstream reservoir operation in the Upper Mun River Basin (UMRB) using the data from 2008 to 2021. Implementing FRBM for UMRB was conducted by identifying two key variables; available water storage and 7–day ahead predicted inflow, as fuzzy inputs. The fuzzy output of the system is the release fraction determined by three operational condition modules; flood, neutral, and drought. For flood module, fuzzy release is primarily determined by the predicted inflow. However, the determination of reservoir release for drought and neutral modules is influenced by the targeted water demand. The results of base case illustrate the capability of FRBM in increasing reservoir storages at the start of dry season by 123.56 MCM/yr in UMRB due to the new daily release schemes generated. This allows supplying water closer to the theoretical agricultural needs and gross irrigation water requirement potentially reducing the risk of water shortfall during consecutive dry years. Whereas, the maximum fuzzy release is constrained corresponding to safe channel capacity of tributaries and Upper Mun river, therefore, downstream flooding is accordingly prevented.

Keywords Fuzzy logic · Fuzzy rule–based model · Artificial intelligence · Upper Mun River Basin

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Introduction

The influence of climate variability on water resource management has intensified flood and drought risks in many regions worldwide. The substantial changes in pattern, quantity and occurrence of hydrological data like rainfall and runoff contributes to the uncertainty of water availability particularly for dam–reservoir system. Since the uneven water supply source in reservoir can be adaptively managed with the effective reservoir operation strategies, therefore, the modern Artificial Intelligence (AI) technologies has been widely adopted to mitigate flood and drought risk damage. In recent years, numerous studies have been devoted to the fuzzy logic applications in hydrology and water resources fields (Kambalimath and Deka 2020). Fuzzy logic, a well–known approach dealing with vagueness and ambiguity, was firstly introduced in 1965 by Prof. L.A. Zadeh (Zadeh 1965; Bai and Wang 2006). It is considered as a subfield of symbolic AI using linguistic representations to solve ambiguous problems. Fuzzy Rule–Based Model (FRBM) which is a specific modeling technique exploiting fuzzy logic approach, has become a constructive and innovative tool due to their ability to handle the uncertainties of hydrological system involved (Bardossy et al. 1995). It has been successfully applied for various specific tasks in water resource management such as single– and multi–purpose single and multiple reservoir operation (Panigrahi and Mujumdar 2000; Mohan and Prasad 2006; Rajendra et al. 2020; Faris et al. 2021), irrigation water allocation (Ibrahim et al. 2018), rainfall– runoff modeling (Hendecha et al. 2001), flood and drought prediction (Pesti et al. 1996; Gogoi and Chetia 2011; Shah 2020; Tabbussum and Dar 2021; Zahran et al. 2023), flood and drought risk assessment (Jiang et al. 2009; Shiravand and Bayat 2023), hydropower generation control (Faris et al. 2021), and groundwater quality and risk assessment (Venkat Kumar et al. 2009; Caniani et al. 2011), etc.

For reservoir operation, FRBMs were successfully developed to derive reservoir operating rules for both single purpose and multipurpose reservoirs to improve efficiency of reservoir operation practice. To model with FRBM for reservoir operation, the reservoir releases were determined in association with reservoir storage level, estimated inflows, and water demand. These achieved research results show the robustness, model performance, and the ease of model construction by fuzzy logic approach for complex reservoir systems (Shrestha et al. 1996).

Additionally, fuzzy rules were dynamically generated for reservoir operation and adjusted to control the amount of reservoir releases based on the relevant factors including reservoir state, inflow, weather forecast, and water use patterns (Mohan and Prasade 2006). Furthermore, the use of fuzzy logic for reservoir operation schemes with reduced rules was suggested to reduce model complexity and redundancy (Sivapragasam et al. 2008). Fuzzy logic–based modelling was also adopted to maximize hydropower production and downstream water demands in semi–arid region. Compared to other techniques such as discrete differential dynamic programming, non–linear programming, and linear programming, fuzzy logic shows increased power production. Importantly, it offers reservoir operators the flexibility and convenience to develop and apply custom fuzzy rules (Faris et al. 2021). FRBM for multi–reservoir operation of two serial reservoirs was developed based on monthly historical operation data. These FRBM results show the success in water resource management by enhancing reservoir operation performances for irrigation, water supply, and hydropower generation. Additionally, the model demonstrates the potential for mapping reservoir manager's experience with fuzzy logic operation (Mohan and Prasad 2006). FRBM, incorporating an optimal set of inflows, storage volumes, and reservoir releases, was integrated with dynamic programming to derive an operating policy for the reservoir system in arid region. This approach achieved good performance in meeting target system performance metrics while maintaining efficient computational requirements (Mousavi et al. 2005). Furthermore, FRBM incorporating a new fuzzy inference system called total fuzzy similarity, was applied for real time reservoir operation. This application highlighted the strong mathematical background of fuzzy inference system for fuzzy reasoning (Dubrovin et al. 2002). These global case studies exhibit the effectiveness of FRBM in solving reservoir operation problems by utilizing fuzzy logic to manage uncertainties and make informed decisions to reservoir operators.

The general work flow of fuzzy logic system consists of four main components; (1) fuzzification, (2) fuzzy rule base, (3) inference engine, and (4) defuzzification (Adnan et al. 2011). Fuzzification stage converts crisp input data into fuzzy sets. These fuzzy sets represent vague concepts with degrees of membership. Membership Functions (MF) is used to specify the degree of membership values (μ) ranging from 0 to 1 for each input value within a fuzzy set. Fuzzy rule–based stage generally collects a set of "if–then" rules that connect input fuzzified values to desired outputs. Experts or data analysis can help define these rules based on domain knowledge or training data. Inference engine evaluates the degree of truth for each activated rule and combines them into a final fuzzy output. Mamdani and Sugeno methods are types of inference engines commonly used in FRBM. Mamdani method proposed by Ebrahim Mamdani in 1975 (Mamdani & Assilian 1975), is suitable when the desired output is qualitative or involves linguistic descriptions. Meanwhile, Sugeno method introduced by Takashi Takagi and Michio Sugeno in 1985 (Sugeno 1985), is efficient when the desired output is numerical and a clear mathematical relationship exists between the input and output variables. Selecting between Mamdani and Sugeno inference engines depend on the specific needs of FRBM and the nature of the desired output. However, the Sugeno inference engine works well with dynamic nonlinear system incorporating optimization and adaptive techniques (Blej and Azizi 2016). Defuzzification is the final stage where the fuzzy output generated by the inference engine is transformed into a crisp value for real world applications. The defuzzification techniques commonly used to convert fuzzy set into a single precise value are Mean of Maximum method (MOM), Center of Gravity method (COG) and the Height Method (HM) (Bai and Wang 2006). The different defuzzification methods exhibit the different performances depending on its applications. Notably, there is no specific defuzzification methods that can achieve desired performance in all conditions (Mogharreban and DiLalla 2006).

In this study, Fuzzy Rule–Based Model (FRBM) was developed for upstream operation of multiple reservoirs in the Upper Mun River Basin (UMRB) where five main dams; Mun Bon (MB), Lamchae (LC), Lam Takhong (LTK), Lam Phraphoeng (LPP), and Lower Lam Chiengkrai (LLCK), are parallelly connected. The fuzzy–based reservoir releases of these dams are yielded to recommend the new daily release schemes for long–term reservoir operation aiming to ensure water security and mitigate flood and drought risks in the region.

Study area

The Mun River Basin (MRB) is a sub–basin of the Greater Mekong River Basin as shown in Fig. 1. It discharges approximately 10% of the river runoff into the Mekong River (Kingston et al. 2011). MRB has suffered seasonally from flooding during wet season (May.–Oct.) and drought during dry season (Nov.–Apr.). In 2022, a large agricultural and residential area particularly in low–lying floodplains along Mun River and tributaries was inundated due to the tropical storm Noru (Bangkok post 2022). Moreover, MRB has regularly experienced severe drought due to substantial variability of rainfall amount leading to crop yield reduction and water shortfall for other demand sectors including water consumption, industrial use and ecology. MRB can be divided into three sub–basins: Upper Mun, Middle Mun, and Lower Mun having diverse characteristics in terms of topography of drainage basin, flow pattern, and land use activities. The Upper Mun River Basin (UMRB) is an upper part of MRB situated mostly in the Khorat Plateau of the northeastern Thailand occupying the drainage area of 16,254 km^2. Operating the dams and reservoirs in UMRB have been carried out by the Royal Irrigation Department (RID) to supply water for both agricultural and non–agricultural needs, such as drinking water, industrial use and ecological need. The total command area for irrigation in UMRB operated by RID is approximately 585.60 square kilometer (km^2). Annual rainfall over the basin ranges between 1,047 and 1,229 millimeters, with more than 74% occurring during the wet season (May.–Oct.). The total annual inflow of the five main dams, representing the water source potential and water availability, varies significantly, ranging from 218 to 1,628 million cubic meters per year (MCM/yr). This deviates considerably from the Annual Water Allocation Plan (AWAP) which is established based on water availability for allocating water to satisfy all demand sectors across the entire basin.

Materials and methods

To achieve the research's goal in mitigating floods and droughts in UMRB, the methodology employed in this study entails three main parts; (1) modelling fuzzy rule–based control in UMRB, (2) developing fuzzy rule–based scenarios for reservoir operation simulation to analyze the flood and drought situations in different perspectives, and (3) evaluating the capability of FRBM for flood and drought mitigation in UMRB.

Modelling fuzzy rule–based control in the Upper Mun River Basin

The Fuzzy Rule–Based Model (FRBM) for multiple reservoir operation in UMRB was formulated based on the physical–based reservoir system as graphically shown in Fig. 2 using long–term data from 2008 to 2021. The daily water balance–based reservoir data and hydrological data collected from the Regional Office 8 of Royal Irrigation Department, Thailand, were used as model inputs. As the controlled releases of each dam in UMRB have been supplied to the local demand downstream, therefore, estimating the agriculture and non–agriculture water needs were carried out and used in the model. The theoretical water demand for agriculture encompassing four operation and maintenance projects was accordingly quantified; Mun Bon and Lam Chae (MB–LCOM), Lam Takhong (LTKOM), Lam Phraphoeng (LPPOM), and Lower Lam Chiengkrai (LLCKOM). The Net Irrigation Water Requirement (NIR) and Gross Irrigation Water Requirement (GIR) with Irrigation Efficiency (IE) of 60% which is regarded as good irrigation, were then estimated as illustrated in the Eqs. (1) and (2).

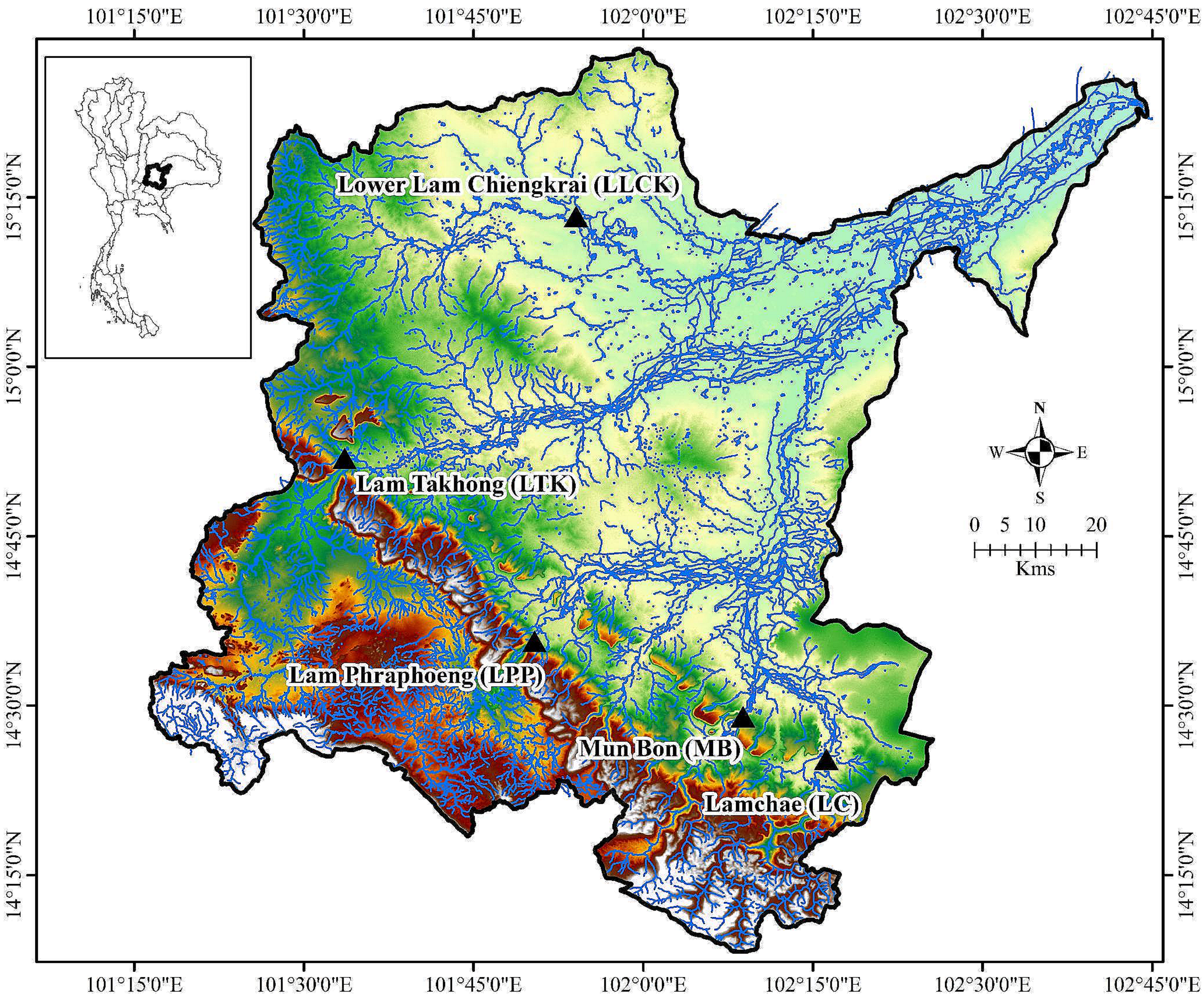

Fig. 1 Map of the Upper Mun River Basin

$$NIR = ETc + PE?RE \tag{1}$$

$$GIR = NIR/IE \tag{2}$$

When *GIR* is gross irrigation water requirement, *NIR* is net irrigation water requirement, *ETc* is theoretical crop water requirement, *PE* is percolation loss, and *RE* is effective rainfall. All variables are in volume unit.

This calculation was based on the average long–term cultivated area of MB–LCOM, LTKOM, LPPOM, and LLCKOM which are 229.83, 144.51, 197.30, and 29.70 km^2, respectively in wet season and 90.97, 64.34, 102.11, and 0.29 km^2, respectively in dry season. For the non–agriculture needs identified in the model, it covers eight nodes of municipality water demand supplied from dams namely, Khon Buri, Pak Thong Chai, Chokchai, Sikhiu, Pakchong, Non Sung, Klong Pahi Prison and Municipal Districts and Nakhon Ratchasima Province which was collected from Provincial Waterworks Authority of Thailand. The amount of diverted water for the industrial use from 2008 to 2021 was collected from private sectors along the rivers. Additionally, ecological water demand was included in the model in association with the established water allocation plan by RID.

The fuzzy rule–based upstream control system for UMRB was developed separately based on single reservoir operation of the five main dams built across river tributaries. However, to maintain downstream flow regulation in FRBM for the multiple reservoir operation system in UMRB, the combined releases from the five dams must be maintained within the safe channel capacity of each river tributaries and UMR, between its minimum and maximum flow constraints before discharging water into the Middle and Lower Mun Rivers. Therefore, data on flow conditions at key gauging

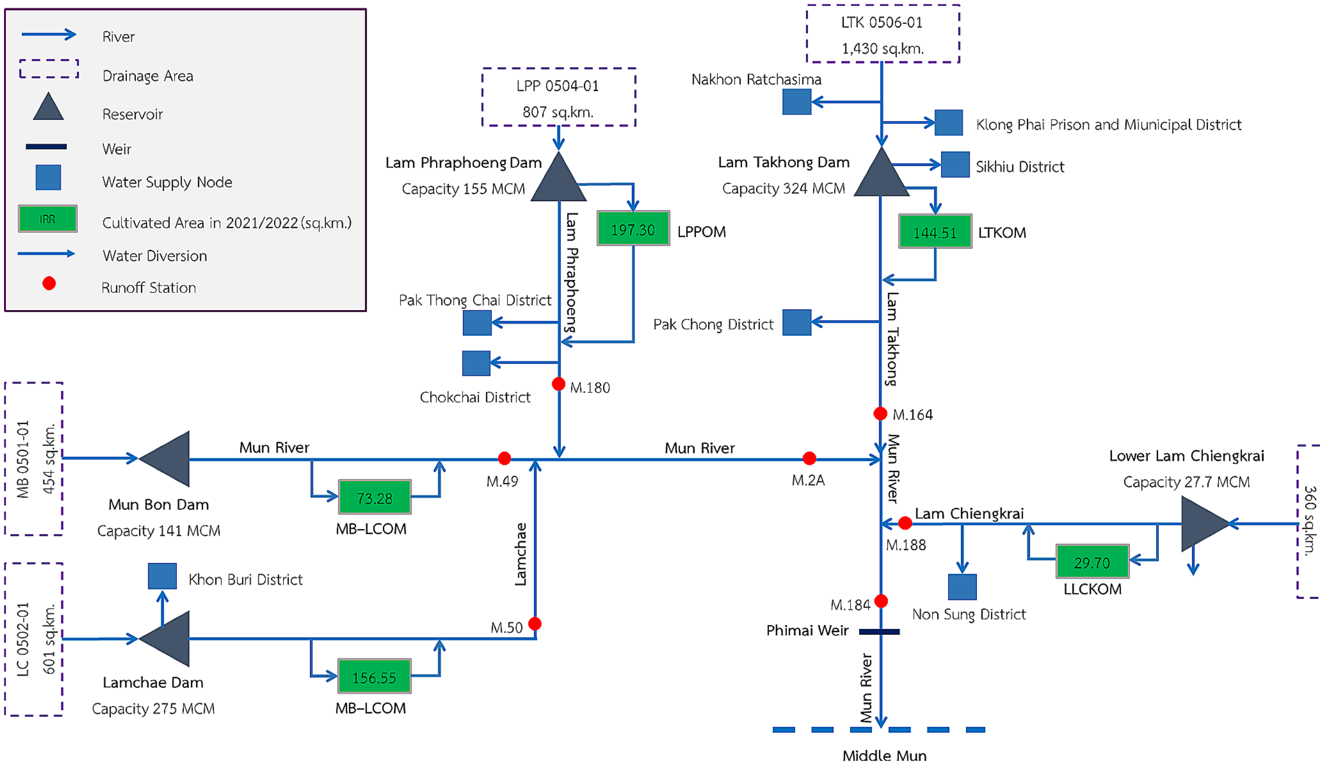

Fig. 2 Schematic diagram of river flow and water supply nodes in the Upper Mun River Basin

stations downstream of all dams along the river were used to identify minimum and maximum flow constraints for the model: M.49 and M.50 for MB–LC dams, M.180 for LPP, M.164 for LTK dams, and M.188 for LLCK dam. Additionally, data at two gauging stations were included for downstream control: M.2 A located downstream of the combined MB–LC–LPP dams, and M.184 situated for downstream control before flowing into the Middle Mun River. In other words, the adjustment of fuzzy releases of all dams was made by considering minimum and maximum flow constraints on its tributary and UMR.

The determination of fuzzy releases from reservoirs by fuzzy rule–based model is based on four main factors: available water storage in reservoirs, 7–day ahead predicted inflow, targeted water demand, and downstream flow condition as illustrated in block diagram in Fig. 3. Fuzzification of two inputs, including available water storage and predicted inflow, was performed to create fuzzy variables. For this study, fuzzification was performed on the inputs of each reservoir. Expert knowledge was used to define the degree of membership functions for each input variable. Membership functions for available water storage were defined as Low (L), Medium (M), High (H), and Very High (VH), considering percentage of active storage. Similarly, the membership functions of predicted inflow (PI) were assigned as Low (L), Slightly Low (SL), Normal (N), Slightly High (SL), and High (H), considering the percentage of the 7–day ahead predicted inflow with respect to maximum historical inflow as expressed in Eq. 3.

$$PI = (Ip * 100) / Imax \tag{3}$$

When PI is predicted inflow in percent, *Ip* refers to 7–day ahead predicted inflow obtained by machine learning technique using XGBoost algorithm and *Imax* represents maximum historical inflow. Both *Ip* and *Imax* are measured in volume unit.

The fuzzy output of the system is specified in term of the release fraction determined by the proposed operational condition modules in association with targeted water demand and percent of predicted inflow. The membership functions for release fraction were defined as Low (L), Slightly Low (SL), Suitable (S), Slightly More (SM), More (M). Once the inputs were fuzzified, a fuzzy operator (AND) combined their membership degrees, representing the degree of fulfillment for the rule's conditions. This degree is then used with the output membership function to obtain a fuzzy output for the rule. In fuzzy logic, when an input value falls within the overlap of two or more membership functions, the corresponding rules are activated. The aggregation method then combines the membership degrees of these activated rules to generate a single output value for the system. Therefore, the equal weighted average method was employed for aggregation in this study.

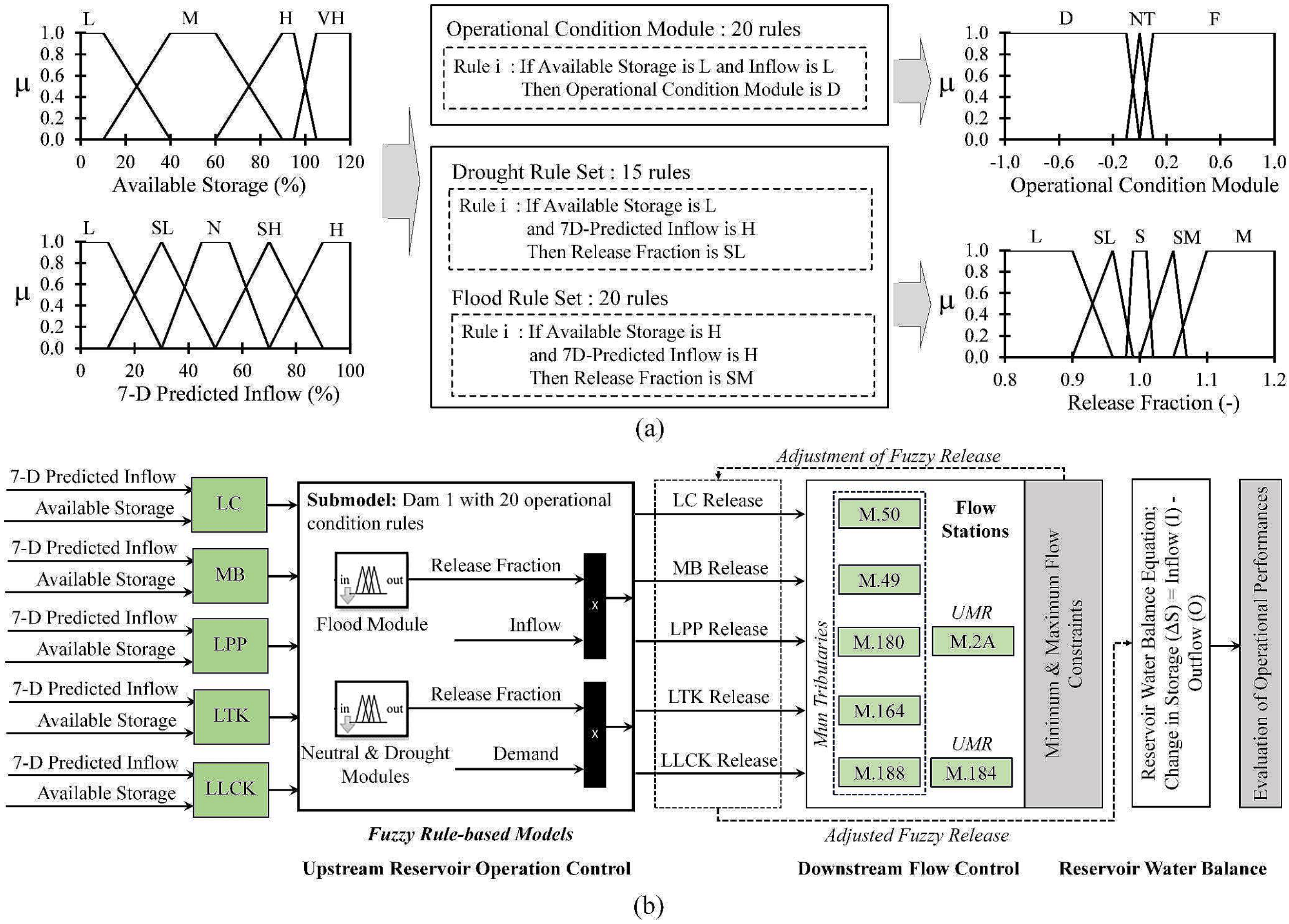

Fig. 3 (**a**) Block diagram of a fuzzy rule–based model (**b**) Upstream reservoir operation control and downstream flow control

To account for seasonal variations in reservoir release control system for flood and drought mitigation, 20 rules of operational condition modules considering the available storage and historical inflow with three linguistic variables: Drought (D), Neutral (NT), and Flood (F), were generated. These variables represent different operating conditions and accelerate the decision–making process through the degrees of membership function of release fraction.

- Drought Module: The determination of reservoir release is strongly influenced by the targeted water demand. Therefore, this module determines a release fraction of 0.8–1.2 of targeted water demand during droughts as expressed in Eq. 4, aiming to fulfil local demand. However, the volume of fuzzy rule–based release is adjusted by increasing to meet the minimum flow requirement when the downstream flow falls below the daily minimum flow required for ecological needs. In drought module, 15 fuzzy rules were generated to specify the reservoir release of each dam.
- Neutral Module: This module specifies a release fraction of 1.0 of the targeted demand indicating normal operating conditions as expressed in Eq. 4. In other words, targeted demand is fully met by the reservoir water without drought or flood risks.
- Flood Module: During flood periods, water release from each reservoir is primarily determined by the predicted inflow and specific downstream flow conditions. Therefore, this module determines a release fraction of 0.8–1.2 of predicted inflow during floods as expressed in Eq. 5, aiming to release water strategically to mitigate flood occurrence. Accordingly, the volume of fuzzy rule–based release is reduced to prevent exceeding the maximum river capacity at the gauging stations. In flood module, 20 fuzzy rules were generated to specify the reservoir release of each dam.

$$R_t = D_t; \mathrm{Droughtandneutralmodules} \tag{4}$$

$$R_t = Ip_t; \mathrm{Floodmodule} \tag{5}$$

When R_t is daily reservoir release volume, d_t is daily targeted water demand volume, Ip is 7–day ahead predicted inflow volume, and α is defuzzified release fraction ranging between 0.8 and 1.2 for flood and drought modules, and 1.0 for neutral module.

The Center of Gravity (COG) method was used for defuzzification process to convert the output fuzzy set into a crisp value of defuzzified release fraction of each dam. MATLAB's fuzzy logic toolbox and Simulink were used to develop a fuzzy logic controller for upstream and downstream operation control in UMRB. Lastly, the fundamental reservoir water balance equation expressing the principle of conservation of mass applied to the water within each reservoir was deployed for long–term reservoir operation simulation in UMRB as shown in Eq. 6.

$$S_{t+1} = S_t + I_t - E_t - R_t \tag{6}$$

When S_{t+1}, S_t is daily reservoir water storage at time t + 1 and t, I_t is daily historical inflow, E_t is daily evaporation losses from reservoir, and R_t is the daily fuzzy–based release.

Developing fuzzy rule–based scenarios for reservoir operation simulation

To develop fuzzy rule–based scenarios for reservoir operation simulation in UMRB, three different scenarios due to distinct types of daily targeted water demand, were accordingly generated; (1) Base Case, (2) Scenario 1, and (3) Scenario 2 as summarized in Table 1. Formulating distinct types of targeted water demand involves considering the current water requirement for UMRB, which can be divided into two parts; (1) agricultural water demand which is the quantity of water required for the irrigation schemes in UMRB as aforementioned and (2) non–agricultural water demand which includes industry and municipality water uses and environmental needs of five main tributaries of Mun Rivers namely, MB, LC, LTK, LPP, and LLCK. Additionally, the Annual Water Allocation Plan (AWAP) from 2008 to 2021 for both agricultural and non–agricultural sectors of five main dams in UMRB established by RID, was used to develop the fuzzy rule–based scenarios, as detailed following.

(1) Base Case: the historically actual controlled releases from five main dams in UMRB were used as targeted water demand for reservoir operation simulation by FRBM.
(2) Scenario 1: both agricultural and non–agricultural water demands used for reservoir operation simulation in UMRB relied on AWAP data.
(3) Scenario 2: an estimate for long–term agricultural water demand in the irrigation schemes representing theoretical water requirement for agriculture was used in FRBM, while non–agricultural demand relied on AWAP data.

In other words, the fuzzy releases were specified based on the different targeted water demand of these three scenarios.

Table 1 Fuzzy rule–based scenarios developed for reservoir operation simulation by FRBM

Scenario	Demand Fuzzification Input			
	Agricultural Water Demand		Non–Agricultural Water Demand	Actual Controlled Release
	Annual Water Allocation Plan	Estimated Demand in Irrigation Scheme	Annual Water Allocation Plan	
Base Case	–	–	–	✓
Scenario 1	✓	–	✓	–
Scenario 2	–	✓	✓	–

Evaluating the capability of FRBM for flood and drought mitigation in UMRB

To evaluate how well FRBM handles drought situation in UMRB, the potential in increasing reservoir water storage of each dam at the start of planting dry season in November, was accordingly examined. The increased reservoir water storage measured as percentage increase indicates the higher potential to satisfy targeted water demand and reduce drought risk in the region. Consequently, average annual water storage and ending water storage in October of all dams was investigated and annual releases were compared with the historical release data. The capability to cope with flood of fuzzy rule–based upstream control system by FRBM was governed by the downstream flow restrictions as aforementioned.

Results and discussion

Specific reservoir data and current water status in UMRB

Detailed information on specific reservoir data and current water status in UMRB including water availability, water requirement, and water allocation are presented in Table 2. Water availability was assessed based on reservoir inflow data from all dams averaged from 2008 to 2021 to unveil the available principal water supply source in the basin. Reservoir release refers to the historical controlled outflow

Table 2 Specific reservoir data and current water status in UMRB averaged from 2008 to 2021

Dam/ Irrigation Scheme	Reservoir Capacity			Reservoir Data			Cultivated Area		Estimated GIR[c]		Water Allocation Plan		
	MPL[a]	NPL[a]	Max. PL[a]	Available Storage	Inflow	Release	Wet Season	Dry Season	Wet Season	Dry Season	Agricultural Water Demand	Non-Agricultural Water Demand	Total
Unit	MCM	MCM	MCM	MCM	MCM	MCM	KM^{2}[b]	KM^{2}[b]	MCM	MCM	MCM	MCM	MCM
MB	7	141	350	76.81	104.11	85.49	216.22	187.03	175.34	202.71	56.75	22.51	79.26
LC	7	275	325	155.31	218.63	178.88					127.44	53.62	181.06
LTK	27	323	367	173.82	279.66	214.40	178.29	115.66	108.44	142.82	131.14	109.75	240.89
LPP	0.72	155.72	242	67.66	193.09	176.11	152.34	112.92	105.86	167.14	89.09	24.87	113.96
LLCK	1.15	27.70	35.82	14.29	86.66	62.34	33.60	0	0	31.50	27.37	1.15	28.52
Total	–	–	–	487.89	882.15	717.22	580.45	415.61	389.64	544.17	431.79	211.90	643.69

Remark: [a] Minimum Pool Level–MPL, Normal Pool Level–NPL, and Maximum Pool Level–Max. PL

[b] Cultivated area of irrigation scheme in 2021

[c] Gross Irrigation Water Requirement (GIR) in 2021 when irrigation efficiency is 60%

volume from each dam, supplying various water demand sectors downstream. The cultivated area size of five irrigation schemes collected in 2021 and the total amount of estimated GIR needed for irrigation were also presented. The water allocation plan established by RID acts as the operational guideline policy for releasing reservoir water to meet demand in practice. However, it can be adjusted to moderate flood and drought risks during the critical periods.

It is revealed that five major dams in UMRB hold an average water availability of 882 MCM/yr, slightly exceeding the average total controlled releases of 717 MCM/yr from all reservoirs. However, water availability of each dam greatly fluctuates over a year. This substantial variation of reservoir inflow leads to flooding at all dams except MB as the average inflow occasionally exceeds their reservoir capacity in critical wet years, raising concerns regarding flood risk water management particularly in 2011, 2013, and 2021. Consequently, heightening the spillway crest to increase the storage volume in some reservoirs like LTK and LPP has been implemented by RID to moderate flooded water by structural measure. Moreover, it is found that only 6.40–22.78% of water availability lies in dry season (Nov.–Apr.) which is much less than the estimated GIR indicating the incapability to supply enough water throughout planting dry season.

The cultivated area in wet season (May.–Oct.) from 2007 to 2021 remained constant at 603.99 km^2, while the dry season area fluctuated substantially, ranging from 0 to 504.44 km^2 as shown in Fig. 4. It is found that the cultivated area size in dry season (Nov.–Apr.) particularly in critical dry years like 2015–2019 is significantly decreased due to limited water availability from reservoirs and less rainfall in dry season.

Moreover, high estimates of Gross Irrigation Water Requirement (GIR) compared to average reservoir releases and AWAP, suggest an increased risk of drought in this region. The total volume of estimated GIR in the irrigation schemes calculated in 2021 is 934 MCM/yr and 58.27% is found in dry season. While the average volume of AWAP is planned to be 644 MCM/yr, meeting agricultural and non–agricultural water demands by 67% and 33%, respectively.

Fig. 5 shows that in normal and wet years during 2009–2011, 2013, and 2020–2021, the water releases from the reservoirs often exceeded AWAP by 19.54–100.93%. Conversely, reservoir releases during the consecutive dry years of 2015–2019 significantly declined by −2.14% to −42.97% compared to AWAP, contributing to a water shortage, especially for the agricultural sector in the region. In addition, the average available storage of five main dams were also explored indicating that the percentages of available water storage are ranged from 43.45 to 56.48% of the total capacity of reservoir. However, the initial storage

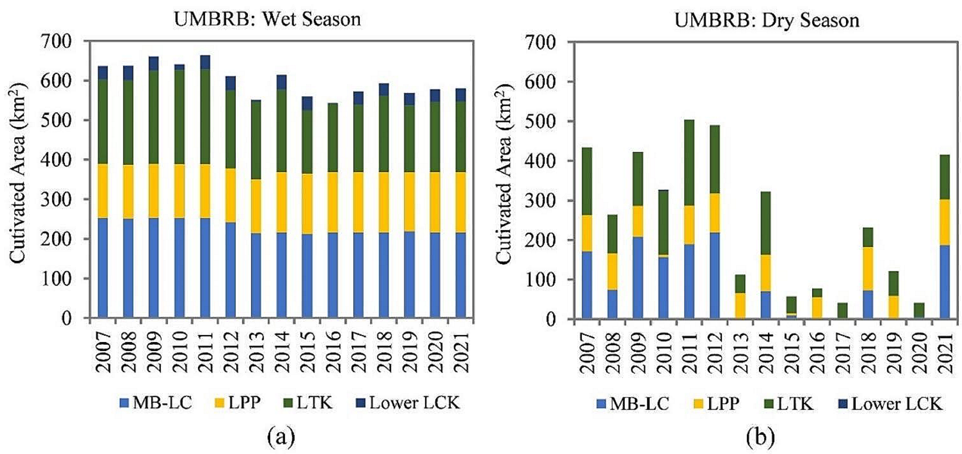

Fig. 4 Cultivated area size in the Upper Mun River Basin from 2007 to 2021 in (**a**) wet season and (**b**) dry season

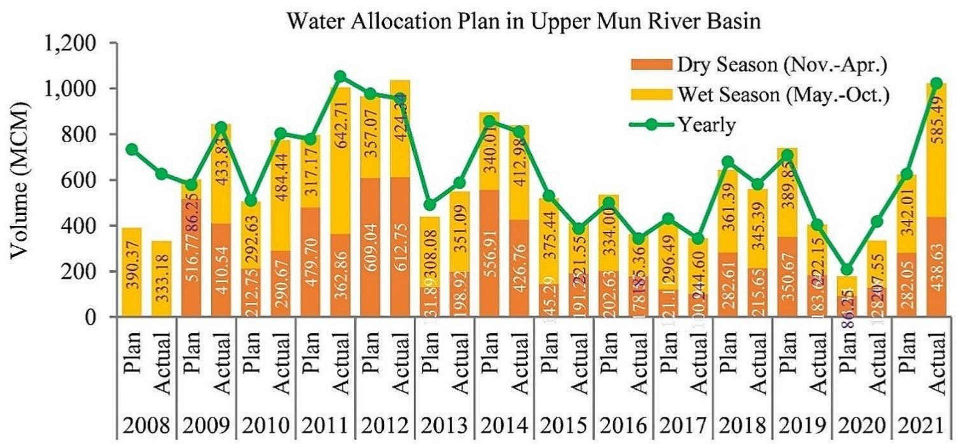

Fig. 5 Water allocation plan and actual releases in the Upper Mun River Basin from 2008 to 2021

significantly decreases at the start of the dry season's cultivation period and slightly increases at the beginning of the wet season's cultivation period. Therefore, altering daily water release pattern by FRBM, a non–structural measure, is aimed to enhance reservoir water storages prior to the dry season for water scarcity alleviation in the region.

Long–term reservoir operation simulation by fuzzy rule–based model

This section analyzes long–term simulation results for multi–reservoir operation in UMRB obtained from the developed fuzzy rule–based model. Three scenarios varying targeted water demand, namely, Base Case, Scenario 1, and Scenario 2 (as detailed in Sect. 2.2), were used for simulation and compared the simulated results with actual reservoir operations from 2008 to 2021. Simulating the base case scenario with a fuzzy rule–based control showed that the daily patterns of fuzzy–based releases for all dams in UMRB differed significantly from those observed in actual reservoir operations particularly in critical dry year (2019) and wet year (2011) as illustrated in Fig. 5. While, the yearly pattern of fuzzy–based releases of all dams closely matched observed releases from all dams as shown in Fig. 6. During critical drawdown periods, fuzzy–based releases prioritize meeting targeted water demand, with defuzzified release fraction from 80 to 120% of targeted water demand. However, the fuzzy releases are modified to maintain the minimum ecological requirement in critical drought periods. Conversely, during critical refilled periods, they prioritize reservoir inflows, with releases ranging from 100 to 120% of 7–D ahead predicted inflow. These releases are further adjusted to avoid exceeding safe channel capacity at key downstream gauging stations along river tributaries and Upper Mun river for flood mitigation.

Fig. 7 presents the long–term fuzzy rule–based simulation results for the base case scenario including average reservoir storage, end–of–wet season (October 31st) and annual releases for each dam. It is revealed that average fuzzy rule–based storages for four main dams; MB, LC, LTK, and LPP dams increased substantially by +53.12%, +1.14%, +25.38%, and +54.49%, respectively. Similarly, the average fuzzy rule–based storage at the end of the wet

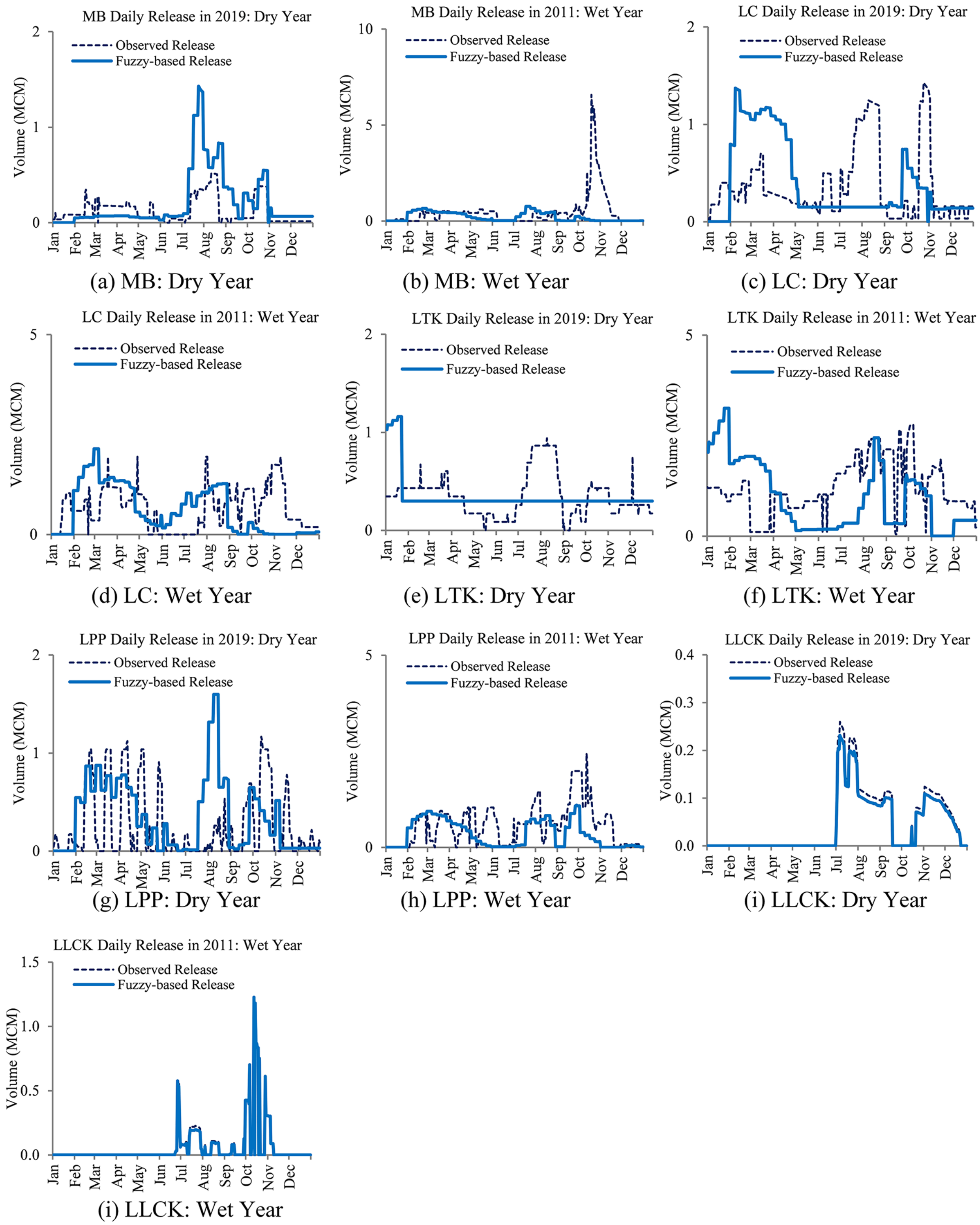

Fig. 6 Daily fuzzy–based releases obtained from base case scenario in critical dry and wet years

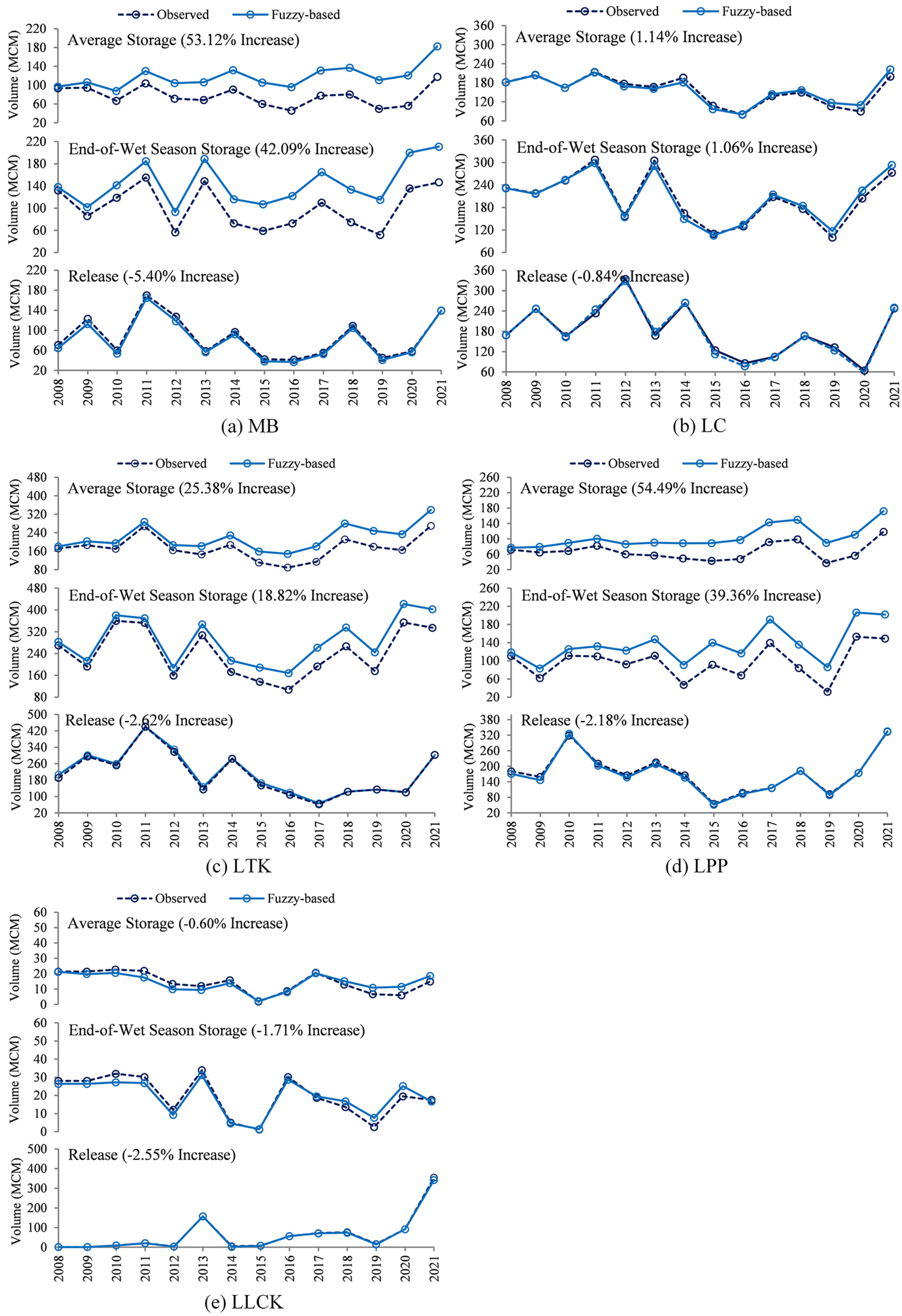

Fig. 7 Long–term annual simulation results for the base case scenario using FRBM

season also increased by +42.09%, 1.06%, 18.82%, and 39.36% for MB, LC, LTK, and LPP dams, respectively. The increased storages at the end of the wet season of these four dams, as a result of the fuzzy rule–based model, signifies a higher initial storage at the start of the dry season to supply potentially for agricultural and non–agricultural needs throughout the dry periods. Additionally, the fuzzy rule–based model can also help slightly decrease the average water storage of LLCK dam by −0.60%. This can help mitigate flood risks at LLCK dam which is recurrently experienced by enormous inflow due to its small reservoir capacity like in 2011 and 2021. Compared to annual actual releases, fuzzy rule–based models suggest slight decreases in water releases from all dams: −5.40% for MB, −0.84% for LC, −2.62% for LTK, −2.18% for LPP, and −2.55% for LLCK. While the annual pattern of fuzzy–release conforms well with the observed one.

This long–term simulation of multi–reservoir operation in UMRB using fuzzy rule–based models suggest their potential to mitigate drought and flood risks in this region. The new daily release schemes generated by FRBM have the potential to increase reservoir storages at the beginning of the dry season of four main dams by approximately 123.56 MCM/yr which 33.02%, 1.44%, 35.71%, and 29.38% are contributed to MB, LC, LTK, and LPP dams, respectively. Furthermore, during the critical dry years from 2014 to 2019, the average fuzzy rule–based storage was significantly greater than the observed storage for MB, LC, LTK, and LPP dams. This allows supplying water closer to the theoretical agricultural needs and GIR (as defined in Scenario 2), potentially reducing the risk of water shortfall during consecutive dry years, as a result of increased available water by fuzzy rule–based models.

Table 3 shows long–term fuzzy rule–based simulation results for scenarios 1 and 2, focusing on reservoir water storage and release compared to actual operations.

Scenario 1 uses a daily targeted water demand based on AWAP. The total amount of planned water demand averaged from 2008 to 2021 is quantified as 643.69 MCM/yr which is substantially lower than the total reservoir releases of 717.22 MCM/yr. This leads the fuzzy rule–based model to recommend different water release schemes for all dams compared to both the actual operation and the base case scenario. However, MB and LPP dams experienced a significant increase in average reservoir storage of approximately +89.31% and +140.52% compared to actual operation. This points out the need to adjust the annual water allocation plans for MB and LPP dams. Specially, increasing the water allocation by +68.60 and +95.07 MCM/yr for MB and LPP dams, respectively is recommended to better reflect current reservoir management of these two dams and enhance its operational efficiency. In contrast, average fuzzy–based storages of LC, LTK, and LLCK dams are likely decreased by −12.65%, −20.10%, and −0.60%, respectively. This signifies the necessity to reevaluate establishing annual water allocation plans for LC, LTK, and LLCK dams. Alternatively, the water allocation for these dams should be reduced by −19.64, −34.94, and −0.09 MCM/yr, respectively to align with the current reservoir operation. However, implementing any adjustment to the strategic water allocation plan requires agreements and consensus between the dam operators and relevant stakeholders particularly a group of farmers in the area who are allocated irrigation water of more than 70% of total demand.

Scenario 2 uses an Estimated Gross Irrigation Water Requirement (EGIR) to determine agricultural water demand representing its theoretical crop water uses and water delivery to five irrigation schemes in UMRB. It then follows the annual water allocation plan for non–agricultural water demand. The calculation in Table 2 shows that total amount of EGIR in wet and dry seasons which is 933.81 MCM/yr, is significantly higher than both the annual water allocation plan and the actual controlled release from all reservoirs which are 643.69 and 717.22 MCM/yr, respectively. This leads to the reduction in average storages for three main dams; MB, LC, and LTK by −2.11%, −30.93%, and −62.96%, respectively, compared to the actual operation. In other words, the total water storage of these three reservoirs was relatively declined by 159.10 MCM/yr due to full potential irrigation supply recommended for this demand scenario. Additionally, this simulated result done by FRBM aligns with the historical evidence that LTK dam historically experienced severe droughts in 2019–2020, LLCK dam in 2014–2016, and LC dam faced reservoir water storage decline in 2013 and 2019–2020. Therefore, these simulated results performed by FRBM suggests that based on EGIR calculation used for non–deficit irrigation, managing proper cultivated area sizes in both wet and dry seasons might be important for good irrigation practice in UMRB. In other words, implementing effective demand side management plan can potentially alleviate crop water stress and help mitigate reductions in crop yield corresponding to water availability.

Conclusion

In tropical region like Thailand, the substantial change of hydrological and climate data driven by the climate variability has led to more frequent and intense floods and droughts. Consequently, effective water resource planning and management measures have become progressively more important. Among the water management measures for flood and drought risks mitigation, strategic reservoir

Table 3 Long–term fuzzy rule–based simulation results for two scenarios

Reservoir	Avg. Observed Storage	Avg. Fuzzy–Based Storage	Avg. Observed Storage at the End of Wet Season[a/]	Avg. Fuzzy–based Storage at the End of Wet Season[a/]	Observed Release	Fuzzy–based Release
Unit	MCM	MCM	MCM	MCM	MCM/yr	MCM/yr
Scenario 1[b/]						
MB–Avg.	76.81	145.40	101.39	173.48	85.49	75.71
MB–Difference		+68.60		+72.09		–9.78
MB–%Increase		+89.31		+71.10		–11.44
LC–Avg.	155.31	135.67	202.68	189.49	178.88	168.32
LC–Difference		–19.64		–13.19		–10.56
LC–%Increase		–12.65		–6.51		–5.90
LTK–Avg.	173.82	138.88	241.57	197.35	214.40	214.79
LTK–Difference		–34.94		–44.22		+0.39
LTK–%Increase		–20.10		–18.30		+0.18
LPP–Avg.	67.66	162.72	97.30	193.53	176.11	114.98
LPP–Difference		+95.07		+96.23		–61.13
LPP–%Increase		+140.52		+98.90		–34.71
LLCK–Avg.	14.29	14.20	19.45	19.11	62.34	60.75
LLCK–Difference		–0.09		–0.33		–1.59
LLCK–%Increase		–0.60		–1.71		–2.55
Scenario 2[b/]						
MB–Avg.	76.81	75.19	101.39	104.65	85.49	86.23
MB–Difference		–1.62		+3.26		+0.74
MB–%Increase		–2.11		+3.21		+0.87
LC–Avg.	155.31	107.28	202.68	167.08	178.88	184.75
LC–Difference		–48.04		–35.60		+5.86
LC–%Increase		–30.93		–17.56		+3.28
LTK–Avg.	173.82	64.38	241.57	139.04	214.40	227.39
LTK–Difference		–109.44		–102.52		+12.99
LTK–%Increase		–62.96		–42.44		+6.06
LPP–Avg.	67.66	79.27	97.30	141.26	176.11	156.75
LPP–Difference		+11.61		+43.96		–19.36
LPP–%Increase		+17.16		+45.19		–10.99
LLCK–Avg.	14.29	15.61	19.45	22.80	62.34	9.71
LLCK–Difference		+1.32		+3.35		–52.63
LLCK–%Increase		+9.23		+17.23		–84.43

Remark: [a/]Ending storage data at the end of wet season evaluated on the 31th October.

[b/]Scenario setting is determined in Table 1

operation is regarded as the effective means to give the detailed decision guidelines for the operators. Since reservoir operation deals with making complicated decisions on uncertain hydrological variables to determine water release, therefore, AI–based constructive tool like fuzzy logic is necessary for decision making process. In this study, a fuzzy rule–based control approach was demonstrated for multi–reservoir operation in the Upper Mun River Basin (UMRB) aiming to mitigate floods and droughts in the region. The fuzzy–based release schemes for three different simulation scenarios varying targeted water demand were generated and presented to illustrate flood and drought solutions by utilizing Fuzzy Rule–Based Model (FRBM) as the operational tool. The results of base case scenario reflecting same current operating conditions indicate that altering the daily release schemes by FRBM, while the annual release volumes are significantly closer to historical outflow, can help increase the total water storage in UMRB by 123.56 MCM/yr. This indicates that allocating reservoir water can be well–operated sufficiently to theoretical crop water demand and other water sectors especially in consecutive dry years especially from 2014 to 2019 due to increased water availability in reservoirs. For downstream flood control by FRBM, the maximum fuzzy release was constrained corresponding to safe channel capacity of river tributaries downstream of all dams, therefore, downstream flooding was accordingly prevented. Additionally, the simulated results performed by FRBM for Scenario 1 incorporating AWAP as targeted water demand, highlight the necessarily to adjust the annual water allocation plans for MB and LPP dams by +68.60 and +95.07 MCM/yr, respectively to better reflect current reservoir management in UMRB. Importantly, the results of Scenario 2 using EGIR as targeted demand, emphasize the importance of controlling the proper size of crop planting areas to balance water availability and demand for the long–term sustainable use of water in the region.

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Declarations

Competing interests The authors have no financial or non–financial interests to disclose.

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