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Mitigating the Impact of Increased Drought-Flood Abrupt Alternation Events under Climate Change: The Role of Reservoirs in the Lancang-Mekong River Basin

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Abstract. The Lancang-Mekong River (LMR) Basin is highly vulnerable to extreme hydrological events, including Drought-Flood Abrupt Alternation (DFAA). The impact of climate change on DFAA and the efficacy of potential mitigation measures such as reservoirs remain poorly understood. This study investigates these dynamics using five Global Climate Models (GCMs) from the Coupled Model Intercomparison Project Phase 6 (CMIP6). It employs the Revised Short-cycle Drought-Flood Abrupt Alteration Index (R-SDFAI), alongside the Tsinghua Representative Elementary Watershed (THREW) model integrated with the developed reservoir module. Results reveal that future DFAA trend varies widely in upstream and downstream, with significant increases respectively in FTD (flood to drought) upstream and DTF (drought to flood) downstream. FTD is more challenging though DTF is more probable to occur. Under SSP126 and SSP245 scenarios, DFAA risks escalate, especially during the wet season, whereas under SSP585, these risks decline. Reservoirs as a promising adaptation strategy can significantly mitigate the year-round DTF and wet season's FTD, particularly in regions with higher total reservoir storage. Reservoir operations reduce DFAA's intensity, limit multiple peaks and shorten its monthly span. Hydrological forecasting and resilient storage enables to be viable options for climate change to help LMR Basin smooth out DFAA. These insights offer valuable guidance for effective water resource cooperative management across LMR Basin countries.

Keywords. Drought-Flood Abrupt Alternation; Climate change; Reservoir operation; Lancang-Mekong River Basin.

1. Introduction

Flood and drought are the two most frequent natural disasters in the world (Adikari et al., 2009;

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ADREM et al., 2024). Drought-Flood Abrupt Alternation (DFAA) served as the rapid transition flood and drought (Xiong et al., 2025) has received growing attention in recent years (Chen et al., 2025; Wu et al., 2023; Zhang et al., 2012; Shan et al., 2018; Song et al., 2023). DFAA is specifically divided into the rapid change from flood to drought (FTD) and from drought to flood (DTF). Hazards arising from DFAA are more significant compared to floods and droughts. DFAA not only alters the soil condition and increases the potential for exceeding water quality standard (Bai et al., 2023; Yang et al., 2019), but also challenges food security and seriously affects agricultural production. Furthermore, DFAA particularly DTF is exposed to triggering severe secondary natural hazards (Wang et al., 2023).

Lancang-Mekong River (LMR) Basin, as an important international river in Southeast Asia, profoundly affects Southeast Asia's important industry sectors such as hydropower, agriculture, fishery and transport (Morovati et al., 2024), while also being the high incidence area of floods and droughts (Liu et al., 2020; MRC, 2020). It is reported that wet season's drought accounts for about 40% of annual drought (Tian et al., 2020) and the potential for large floods happening in dry season (e.g., May 2006, May 2007, and December 2016) (Tellman et al., 2021). These non-negligible wet season's drought and dry season's flood are all prerequisites for DFAA.

Continued global warming will further exacerbate extreme wet and dry climate (IPCC, 2023) and contribute to the increased vulnerability of DFAA in future (Yang et al., 2022; Wang et al., 2023; Chen et al., 2025). There is a strong tendency of intensifying floods and droughts in Southeast Asia (IPCC WG1, 2021) as well as in LMR Basin (Wang et al., 2021; Li et al., 2021; Dong et al., 2022; Hoang et al., 2016). This warns of the serious DFAA pattern in LMR Basin and puts forward new requirements for water security and sustainable management, especially the early disaster forecasting and prevention system.

The hydrological regime of LMR Basin is influenced by two main drivers, climate change and human activity (LMC and MRC, 2023). Despite the severity of climate change impacts, human activity is capable of adapting climate change on hydrological regime in LMR Basin (Zhang et al., 2023; Khadka et al., 2023; Sridhar et al., 2019; Lu et al., 2014; Gunawardana et al., 2021), such as reservoir operation. Previous studies revealed that reservoirs play an effective role in suppressing flood magnitude, reducing flood frequency and decreasing low flow events (Wang et al., 2017b; Yun et al., 2021b; Dang et al., 2024), suggesting reservoirs represent the powerful approach to combat climate change.

It is crucial to consider the adaptation role of human activities, represented by reservoirs, under climate

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change to DFAA, which helps managers to develop effective policies on water resource management and ensures sustainable development of basin system. However, little attention has been paid to this aspect for LMR Basin in previous studies. The statistic, report, and study related to DFAA in LMR Basin are almost empty currently, let alone the impact of climate change and the mitigating role of reservoirs on DFAA. Therefore, this study develops the reservoir module for hydrological modelling, highlights the trend of DFAA in LMR Basin under climate change, and explores how reservoirs assist basin states to adapt changing climate. It endeavors to generate new knowledge into DFAA and contributes to water resource management and regional sustainability.

2. Methodology

2.1 Study area

The Lancang-Mekong River (LMR) originates from the Tibetan Plateau in China and flows through China, Myanmar, Laos, Thailand, Cambodia, and Vietnam before entering the South China Sea at Mekong delta. LMR is approximately 4900 km long, with the basin area of 812400 km^2 (He, 1995), and its annual runoff is approximately 475 billion m^3. LMR Basin is characterized by steep slopes and rapid flows in upstream, along with shallow slopes and slow mixed flows in downstream. The wet and dry seasons in LMR Basin extends from June to November and from December to May (LMC and MRC, 2023), which are mainly influenced by southwestern and northeastern monsoons respectively. The distribution of the hydrology system and mainstream hydrological stations in LMR Basin are detailed in Fig. 1a.

LMR Basin nourishes approximately 65 million people. The basin states rely on the river system to develop economic industries including capture fishery, irrigation agriculture, and hydropower. LMR Basin has the largest freshwater capture fishery in the world (MRC, 2010; MRC, 2019), and its irrigation area is estimated around 4.3 million hectares (Do et al., 2020), with the Mekong Delta regarded as Southeast Asia's food basket. LMR Basin is one of the most active regions for hydropower in the world (MRC, 2019; Williams, 2019), harboring about 235,000 GWh · yr^{-1} of hydropower potential in its mainstream and tributaries (Do et al., 2020; Schmitt et al., 2018). LMR Basin meanwhile is heavily impacted by flood and drought. During past two decades, LMR Basin has experienced several severe droughts (2004-2005, 2009-2010, 2015-2016, and 2019-2020) and floods

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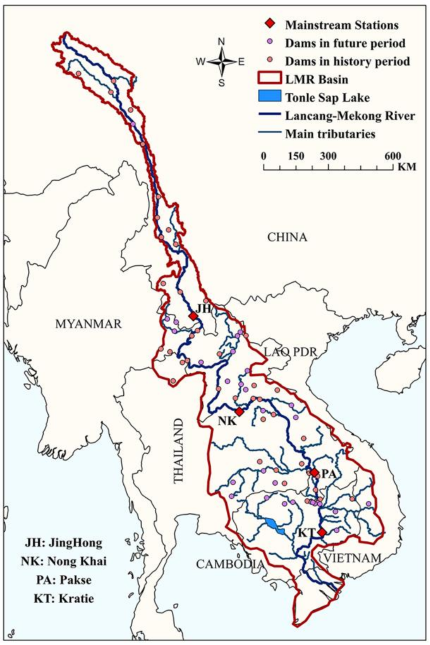
(Liu et al., 2020; Tian et al., 2020; MRC, 2020), which bits crop cultivation and fishery harvesting, causing loss of property and lives in riparian countries. Floods of 2013 and 2018 heavily affected lower basin (Cambodia, Vietnam, Laos, and Thailand), covering 22.3 and 6.47 thousand km^2 respectively (Tellman et al., 2021).

(a)



(b)

	Country	Cumulative area (km^2)
JingHong	China	143,647
Nong Khai	Thailand	310,265
Pakse	Lao PDR	553,221
Kratie	Cambodia	646,000

(c)

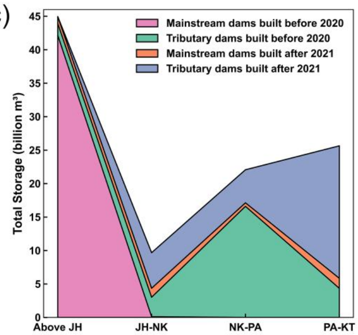


Figure 1: Hydrology of LMR Basin. (a) Map of rivers and reservoirs, (b) Information of four main hydrological stations, and (c) distribution of reservoir storage. Note that JH, NK, PA, and KT respectively denote JingHong, Nong Khai, Pakse, and Kratie stations.

2.2 Data collection

This study utilizes CMIP6 (Sixth Phase of Coupled Model Inter-comparison Project) data as the meteorological input to analyze DFAA. Three SSP (Shared Socioeconomic Pathways) scenarios, namely SSP1-2.6, SSP2-4.5, and SSP5-8.5 (hereafter referred to SSP126, SSP245, and SSP585), are considered to characterize the low-, medium-, and high-emission scenarios respectively. Five GCMs (Global Climate Model) with widely utilization in LMR Basin are applied in this study (Yun et al., 2021a; Yun et al., 2021b), i.e., GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL. The detailed information for these five GCMs is shown in Table 1 (Eyring et al., 2016; Gidden et al., 2019; Cui et al., 2023). CMIP6 data span from 1980 to 2100. This study accordingly considers three research periods, namely history period from 1980 to 2014 (consistent with CMIP6),

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near future period from 2021 to 2060, and far future period from 2061 to 2100.

In this study, the daily observed runoff data at four major mainstream hydrological stations from 1980 to 2020 serve to calibrate and validate the hydrological model, which are derived from China Meteorological Administration (CMA) and Mekong River Commission (MRC). The hydrological stations from upstream to downstream are sequentially JingHong, Nong Khai, Pakse and Kratie, whose location and basic information are shown in Figs. 1a and 1b. This study treats the ERA5_Land data as the meteorological input when calibrating and validating the hydrological model, and as the correction dataset when correcting the raw CMIP6 data. ERA5_Land data cover the period from 1980 to 2020, with the spatial resolution of 0.1°, and contain precipitation, temperature, and potential evapotranspiration. Soil data are obtained from the Global Soil Database (GSD) provided by the Food and Agriculture Organization of the United Nations (FAO) with the spatial resolution of 10 x 10 km. Normalized Vegetation Index (NDVI), Leaf Area Index (LAI) and Snow Cover are obtained from MODIS (Moderate-resolution Imaging Spectroradiometer) with the spatial resolution of 500 x 500 m and the temporal resolution of 16 days.

Reservoir data are sourced from MRC and Mekong Region Futures Institute (MERFI) (MERFI, 2024). 122 reservoirs which simultaneously contain information on location, storage and operation year are utilized in this study, including 24 reservoirs in Lancang Basin and 98 reservoirs in Mekong Basin. The earliest and latest operation years for them are 1965 and 2035. The location and storage distribution of these reservoirs are shown in Figs. 1a and 1c.

Model Name	Modeling Center	Realization	Resolution (Lon×Lat)
GFDL-ESM4	National Oceanic and Atmospheric Administration Geophysical Fluid Dynamics Laboratory, United States	r1i1p1f1	1.25°×1°
IPSL-CM6A-LR	Institute Pierre Simon Laplace, France	r1i1p1f1	2.5°×1.25874°
MPI-ESM1-2-HR	Max Planck Institute for Meteorology, Germany	r1i1p1f1	0.9375°×0.9375°
MRI-ESM2-0	Meteorological Research Institute, Japan	r1i1p1f1	1. 125°×1. 125°
UKESM1-0-LL	Met Office Hadley Centre, UK	r1i1p1f2	1.875°×1.25°

Table 1: Details of 5 GCMs applied in this study.

2.3 Bias correction method for CMIP6 data

The raw CMIP6 data require correction for more accurate modelling (Hoang et al., 2016; Mishra et al., 2020; Sun et al., 2023). The uncorrected raw CMIP6 data misestimate the temperature and precipitation in LMR Basin, especially overestimating the precipitation (Cui et al., 2023; Lange et al., 2019; Lange

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et al., 2021). ERA5_Land data are applied as the correction data in this study to correct bias in raw CMIP6 data.

This study interpolates the five GCMs data of CMIP6 with different spatial resolutions to 0.1° (consistent with ERA5_Land) based on the bilinear interpolation spatial resolution method. The interpolated CMIP6 data are bias-corrected for each GCM according to N-dimensional probability density function transform of the multivariate bias correction approach (abbreviated as MBCn) (Cannon, 2016; Cannon, 2018). The MBCn method is trained based on the difference between precipitation and temperature data from ERA5_Land and CMIP6 over history period (1980-2014), and then applied to future period (i.e., 2021-2100) to correct the CMIP6 data for each GCM.

The MBCn method considers the multivariate dependency structure of meteorological data and enables the simultaneous correction of temperature and precipitation data. It demonstrates a significant improvement in terms of correction precision and accuracy, compared to uni-variate bias correction algorithms along with other multivariate bias correction algorithms (Cannon, 2018).

2.4 Hydrological model coupled with reservoir module

THREW (Tsinghua Representative Elementary Watershed) hydrological model is applied in this study for runoff simulation, which delineates basin based on the Representative Elementary Watershed (REW) method (Tian et al., 2006; Mou et al., 2008). It's constructed following scale coordinated equilibrium equations, geometrical relationships and constitutive relationships, and enables to comprehensively simulate complex hydrological processes from mountain to ocean. The automatic calibration procedure is employed in THREW model to calibrate hydrological parameters through parallel computation (Nan et al., 2021). The calibration period of THREW model in LMR Basin is from 2000 to 2009, and the validation period is from 2010 to 2020. The Nash efficiency coefficient (NSE) indicator is adopted to calibrate objective function and evaluate simulation effectiveness at daily scale, which is calculated according to Eq. (1). THREW model has been successfully applied to a number of basins with vary climate characteristics worldwide (Tian et al., 2012; Lu et al., 2021; Morovati et al., 2023; Cui et al., 2023; Zhang et al., 2023).

$$NSE = 1 - \frac{\sum_{n=1}^{N}(Q_o^n - Q_s^n)^2}{\sum_{n=1}^{N}(Q_o^n - \overline{Q_o})^2} \tag{1}$$

Where, Q_o^n is the daily observed runoff, Q_s^n is the daily simulated runoff, $\overline{Q_o}$ is the average of

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observed runoff, and N is the total number of days.

The reservoir module of THREW model developed in this study considers the annual storage change and operates reservoirs according to the REW format. Each reservoir is assigned to the corresponding REW based on its location. The cumulative multi-year storage of each REW is calculated annually, and the reservoir is scheduled accordingly by year and REW. The reservoir module consists of two parts, i.e., the initial phase and the normal phase.

When the cumulative multi-year storage of some REW changes in one year, it indicates that at least one new reservoir starts operation in that REW in that year. The additional reservoir operates under the initial phase rules. The rules for initial phase are described as Eqs. (2) to (4). The outlet flow is equal to the inlet flow if the inlet flow is less than the minimum discharge constraint, and otherwise equal to the minimum discharge constraint. Constraints on storage and discharge are summarized in Eqs. (5) to (6) (Tennant, 1976; Yun et al., 2020). The ending condition for initial phase is Eq. (7). When the storage of the additional reservoir is larger than the minimum storage constraint, end the initial phase and enter the normal phase.

$$Q_{out} = \begin{cases} Q_{in}, Q_{in} < Q_{min} \\ Q_{min}, Q_{in} \geq Q_{min} \end{cases} \tag{2}$$

$$S_t = S_{t-1} + Q_{in} - Q_{out} \tag{3}$$

$$S_0 = 0 \tag{4}$$

$$S_{min} = 0.2 \times S_{total} \tag{5}$$

$$Q_{min} = 0.6 \times Q_{ave} \tag{6}$$

$$S_t \geq S_{min} \tag{7}$$

Where Q_{out} is the outlet flow, Q_{in} is the inlet flow, Q_{min} is the minimum discharge constraint, S_t is the storage for time t, S_{min} is the minimum storage constraint, S_{total} is the total storage, and Q_{ave} is the average multi-year runoff during calibration period (i.e., 2000-2009).

The scheduling rule for normal phase is the improved Standard Operation Policy hedging model (SOP) (Wang et al., 2017a; Morris & Fan, 1998), as depicted in Eqs. (8) to (12). Under the premise of water balance, constraints for annual storage, outlet flow, wet season storage, and dry season storage are considered separately, where priority is given to the annual storage constraint (Eq. (9)).

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$$S_t = S_{t-1} + Q_{in} - Q_{out} \tag{8}$$

$$S_{min} \leq S_t \leq S_{max} \tag{9}$$

$$Q_{min} \leq Q_{out} \leq Q_{max} \tag{10}$$

$$\min|S_c - S_t|, \text{month} = 6,7,8,9,10,11 \tag{11}$$

$$\min|S_n - S_t|, \text{month} = 12,1,2,3,4,5 \tag{12}$$

Where Q_{max} is the maximum discharge constraint, S_{max} is the maximum storage constraint, S_c is the storage corresponding to the flood control level, and S_n is the storage corresponding to the normal storage level.

The constraint for normal phase is further classified into the general case and the emergency case. The reservoir scheduling rules are the same for two cases, but constraints for the emergency case are more relaxed. When the reservoir enters the normal phase, constraints of the general case are used by default. Constraints for the general case are given in Eqs. (13) to (18). After scheduling according to general case's constraints, if the outlet flow constraint is not fully satisfied (Eq. (10)), constraints are adjusted to that in the emergency case and the reservoir is re-operated following adjusted constraints. Eq. (19) characterizes the start condition for the emergency case. The emergency case is set to avoid excessive high or low outlet flow caused by the strict constraints. Constraints of the emergency case are shown in Eqs. (20) to (21).

$$Q_{max} = 2 \times Q_{ave} \tag{13}$$

$$Q_{min} = 0.6 \times Q_{ave} \tag{14}$$

$$S_c = S_{min} \times 1.2 \tag{15}$$

$$S_n = S_{max} \times 0.8 \tag{16}$$

$$S_{min} = 0.2 \times S_{total} \tag{17}$$

$$S_{max} = \begin{cases} 0.8 \times S_{total}, \text{month} = 6,7,8,9,10,11 \\ 1 \times S_{total}, \text{month} = 12,1,2,3,4,5 \end{cases} \tag{18}$$

$$Q_{min} \leq Q_{out}' \leq Q_{max} \tag{19}$$

$$Q_{min} = 0.3 \times Q_{ave} \tag{20}$$

$$S_{max} = 0.8 \times S_{total} \tag{21}$$

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Where Q_{out}' is the outlet flow after the scheduling in general case.

Based on CMIP6 data of 5 GCMs under 3 SSPs, THREW model coupled reservoir module is applied to simulate runoff at mainstream hydrological stations under scenarios with and without reservoir operations for history, near future, and far future periods. Then the R-SDFAI indicator (described in Sections 2.5) is utilized to calculate DFAA's probability for three study periods. The results are presented as the average of 5 GCMs to reduce the uncertainty arising from GCMs, especially from the prediction of precipitation (Hecht et al., 2019; Hoang et al., 2016). This study adopts the difference in DFAA's probability between natural (without reservoir operations) and dammed scenarios (considering reservoir operations) to capture reservoir's impact, as shown in Eq. (22).

$$\text{Impact of Reservoir} = P_{dammed} - P_{natural} \tag{22}$$

Where $P_{natural}$ and P_{dammed} denote respectively the probability without and with reservoir operations.

2.5 Indicator for DFAA

Since Wu (2006) proposed the precipitation based long-cycle drought-flood abrupt alternation index (LDFAI) to quantitatively characterize the long-term DFAA of wet season, LDFAI has been widely adopted (Ren et al., 2023; Shi et al., 2021; Yang et al., 2022; Yang et al., 2019). Zhang (2012) proposed the one-month interval short-cycle drought-flood abrupt alternation index (SDFAI) based on LDFAI to characterize the short-term DFAA of wet season, and expanded the application from precipitation to runoff. SDFAI has been extensively applied in various fields such as hydrology, meteorology, ecology, and agriculture (Zhao et al., 2022; Lei et al., 2022; Yang et al., 2019; Zhang et al., 2019). However, SDFAI still suffers from over and missed recognition of DFAA, along with incorrectly reflecting DFAA severity. The Revised Short-cycle Drought-Flood Abrupt Alteration Index (R-SDFAI) proposed by Song et al. (2023) portrays short-cycle DFAA based on Standardized Runoff Index (SRI), which well avoids problems in SDFAI. Moreover, the applicable period of R-SDFAI is expanded from wet season to the whole year, which facilitates the multi-year analysis on DFAA.

This study adopts R-SDFAI for DFAA analysis. The formulas for R-SDFAI are summarized in Eqs. (23) to (28).

$$F_1 = S_{i+1} - S_i \tag{23}$$

$$F_2 = |S_{i+1}| + |S_i| \tag{24}$$

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$$F = \left|\frac{F_1}{F_2}\right|^{|S_{i+1}+S_i|} \tag{25}$$

$$I = F \times \min(|S_{i+1}|, |S_i|) \tag{26}$$

$$I' = \left(\frac{I}{0.5}\right)^{\frac{\max(|S_{i+1}|,|S_i|)^2}{|F_1|+F_2}} \times \frac{I^{\frac{\max(|S_{i+1}|,|S_i|)}{|F_1|+F_2}} + I^{\frac{\min(|S_{i+1}|,|S_i|)}{|F_1|+F_2}}}{2} \tag{27}$$

$$R - SDFAI = \mathrm{sign}(F_1) \times \left(\frac{I'}{I'_{0.5}} \times \frac{I}{0.5}\right)^{\left[\frac{\max(|S_{i+1}|,|S_i|)}{|F_1|+F_2}\right]^{\left[1-\frac{\max(|S_{i+1}|,|S_i|)}{|F_1|+F_2}\right]}} \tag{28}$$

Where, S_i refers to the SRI in month i, F1 denotes the intensity of DFAA, F2 denotes the absolute intensity of drought and flood, and F is a weighting factor between 0 and 1. $I'_{0.5}$ refers to I' when I=0.5.

The threshold for R-SDFAI to identify DFAA is ± 1 (Song et al., 2023). When R-SDFAI > 1, DTF occurs, and when R-SDFAI < -1, FTD occurs.

3. Result

3.1 CMIP6 data bias correction performance

The uncorrected raw CMIP6 data exhibit large bias during history period (1980-2014) at both spacial and seasonal scales. Compared with ERA5_Land data for history period, the uncorrected raw CMIP6 data deviate by $\pm$1800 mm in average annual precipitation and by $\pm$12℃ in average daily temperature (Figs. 2b and 2e). It demonstrates that utilizing uncorrected raw CMIP6 data for hydrological simulation will generate severe inaccuracy. However, CMIP6 data corrected by MBCn method deviate from ERA5_Land within 120 mm of average annual precipitation and $\pm$0.2 ℃ of average daily temperature (Figs. 2c and 2f). The bias correction significantly improves the accuracy of CMIP6 data in LMR Basin. Meanwhile, the corrected CMIP6 data match the seasonal cycle of ERA5_Land well in both precipitation and temperature (Fig. 2g). With respect to raw CMIP6 data before correction, the spatial and temporal distribution accuracy of corrected CMIP6 improves dramatically, which contributes to more accurate and reasonable analyses for DFAA.

3.2 Calibration and validation for hydrological model

The daily observed runoff versus daily simulated runoff given by THREW model for calibration period (2000-2009) and validation period (2010-2020) are illustrated in Fig. 3. Since there was no massive

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reservoir construction in LMR Basin before and during calibration period (Zhang et al., 2023), THREW model without reservoir module is modeled for calibration period. Meanwhile, part of large scale reservoirs have been commissioned during validation period, thus THREW model with reservoir module is validated in validation period. THREW model captures the runoff fluctuation between wet and dry seasons well, with the NSE of at least 0.8 during calibration and validation periods. THREW model exhibits excellent simulation performance in both upstream and downstream.

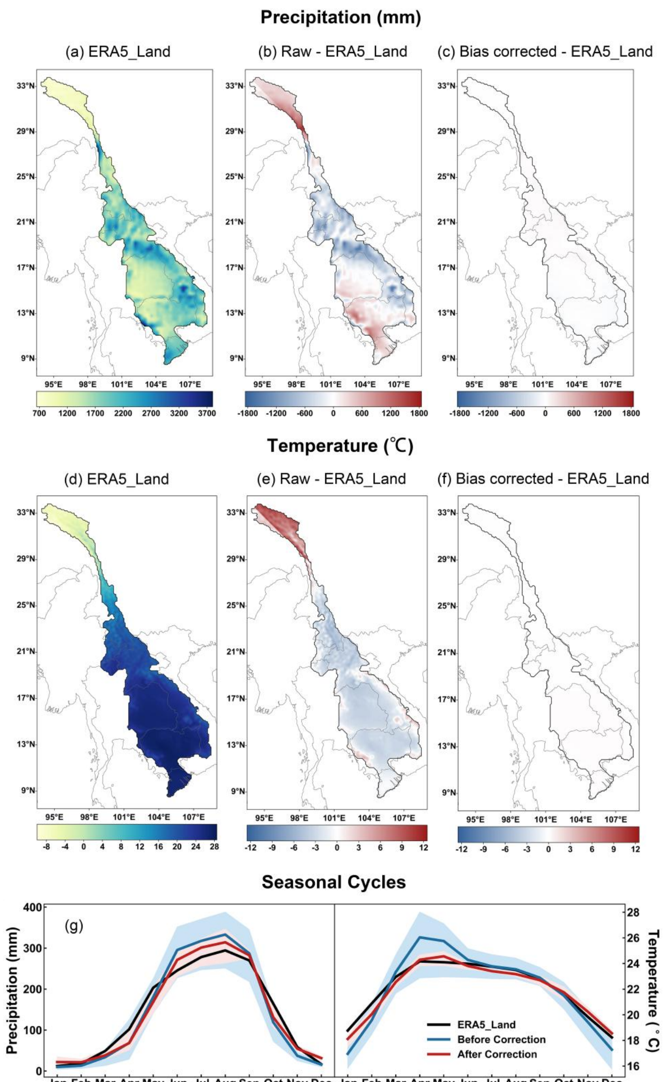

Figure 2: Averaged meteorological data of 5 GCMs for history period (1980-2014). Note that 5 GCMs are corrected separately. (a)-(c) present the spatial distribution of precipitation based on respectively

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ERA5_Land, raw CMIP6 (raw CMIP6 minus ERA5_Land) and bias-corrected CMIP6 (bias-corrected CMIP6 minus ERA5_Land). (d)-(f) illustrate the spatial distribution of temperature based on ERA5_Land, raw CMIP6 (raw CMIP6 minus ERA5_Land) and bias-corrected CMIP6 (bias-corrected CMIP6 minus ERA5_Land). (g) seasonal cycles of temperature and precipitation from ERA5_Land, raw and bias-corrected CMIP6, as well as their corresponding range.

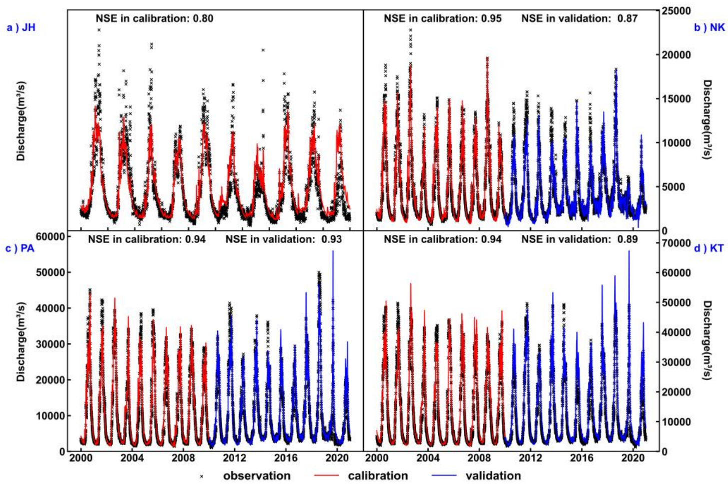

Figure 3: Performance of THREW model in calibration (2000-2009) and validation (2010-2020) periods. Note that JH, NK, PA, and KT denote JingHong, Nong Khai, Pakse, and Kratie stations, respectively.

3.3 DFAA under changing climate

Under natural scenario (without reservoir operations), DFAA in LMR Basin is dominated by DTF, i.e., the risk of DTF is more critical than that of FTD. DFAA risk moreover is significantly higher in wet season than dry season (Fig. 4a). The FTD probability in wet season is 2 to 5.5 times higher than dry season in history period. In near and far future, this ratio respectively ranges from 1.1 to 36 times and 3.3 to 41 times. As for DTF, the probability in wet season is correspondingly 1.7 to 5.7 times, 1.3 to 3.9 times and 0.9 to 6.3 times higher than that in dry season for history, near future and far future. Only JingHong station experiences a slightly higher probability of DTF in dry season (1.25%) than wet season (1.17%) for far future. Furthermore, the annual probability in DFAA is higher remarkably downstream than upstream (Fig. 4a). The annual FTD's probability ranges from 1.1.% to 2.5% at JingHong station and 1.3% to 2.8% at Nong Khai station, which rises to 2.3% to 4.2% and 2.7% to 4.1% at Pakse and Kratie stations. Similarly, the annual DTF's probability at JingHong and Nong Khai stations are 2.4% to 4.1% and 2.3% to 4.5%, while those at Pakse and Kratie stations reaches 3.7% to 6.3% and 4.2% to 6.3%. The DTF risk in wet season and FTD risk in both dry and wet seasons are also

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higher downstream than upstream. Since the FTD probability in dry season at Nong Khai, Pakse and Kratie stations is limited, especially under SSP585 (<0.2%), the FTD risk of dry season is exhibited as more notable upstream than downstream.

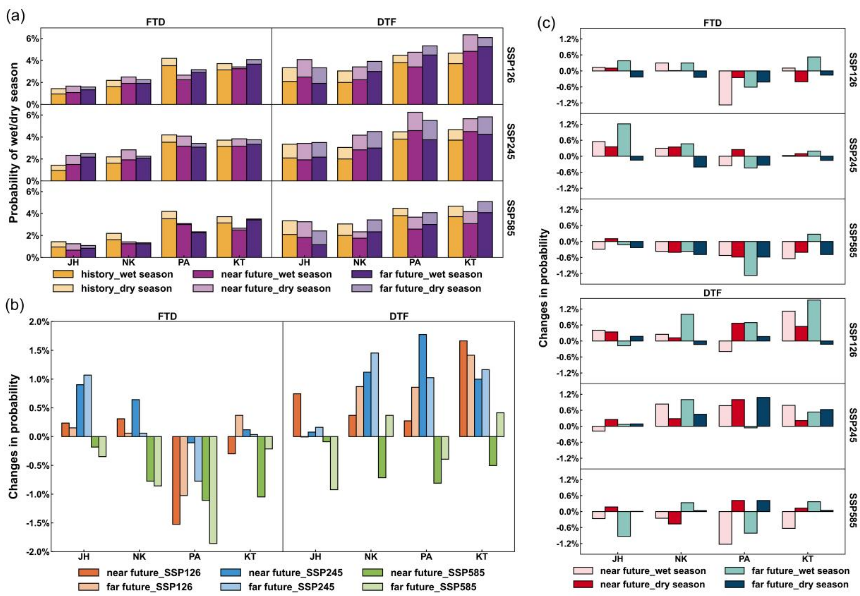

Figure 4: DFAA under natural scenario. Note that JH, NK, PA, and KT respectively denote JingHong, Nong Khai, Pakse, and Kratie stations. (a) Seasonal probability of DFAA during history (1980-2014), near future (2021-2060) and far future (2061-2100) periods, as well as under three SSPs. The annual probability is half of the sum of wet and dry season probabilities. (b) The annual change in DFAA probability in near future and far future with respect to history period under three SSPs. (c) The seasonal change in DFAA probability in near future and far future with respect to history period during wet and dry seasons under three SSPs.

The annual DFAA risk increases under SSP126 and SSP245 (except for FTD at Pakse station) and decreases under SSP585 (Fig. 4b). SSP585 represents the least prone to DFAA of three scenarios, under which the FTD probability ranges from 1.1% to 3.5%, and the DTF probability varies from 2.3% to 5.1%. SSP245 is the scenario with the highest DFAA risk, with probability ranging from 1.4% to 4.1% and 3.4% to 6.3% for FTD and DTF respectively. Further, the future growth in DTF exceeds significantly that of FTD, with more pronounced rising risk of FTD in upstream and DTF in downstream. The future DTF probability at JingHong station versus history period is -0.4% to 1.1%, at Nong Kai station is -0.9% to -0.6%, and at Pakse and Kratie stations respectively is -1.9% to -0.1% and -1% to 0.4%. The change of future FTD probability for JingHong is -0.9% to 0.2%, while it is -0.7% to

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1.5%, -0.8% to 1.8%, and -0.5% to 1.7% for Nong Khai, Pakse and Kratie, respectively. The opposite trends of DFAA risk in upstream and downstream pose the enhanced challenge to the integrated management of LMR Basin. The DFAA risk meanwhile increases most significantly under SSP245, while under SSP585 FTD risk drops and the growth of DTF risk is also negligible. Similar to the annual DFAA risk, the wet season risks for both DTF and FTD rise under SSP126 and SSP245, and fall under SSP585 (Fig. 4c). The FTD risk in dry season reduces, with the exception of an increase (<0.4%) under SSP245 in near future. The dry season risk for DTF rises in all situations apart from a decrease of 0.46% at Nong Khai station under SSP585 in near future. The largest increase occurs at Pakse station under SSP245 which reaches 1.08%.

3.4 Reservoirs impacts on DFAA

The reservoir exhibits extraordinary mitigation effects on DTF risk under changing climate while weaker effects in FTD risk. (Fig. 5a). Nonetheless, the higher probability of DTF compared to FTD (Fig. 4a) demonstrates that the reduction effect of reservoirs on DFAA is significant. Reservoirs adequately alleviate the future DTF probability (-0.13% to 1%), with only slightly growth at Nong Khai station in near future under SSP126 (Fig. 5a). Reservoirs exhibit better mitigation effects in near future at JingHong station. As for Nong Khai and Pakse stations, The reduction effect of reservoir on DTF is more pronounced in far future under SSP126 and SSP245 while in near future under SSP585. It's conversely stronger in near future under SSP126 and SSP585 at Kratie station while in far future under SSP245. The reduction effect of reservoir on FTD performs slightly better in near future (0.42%) than far future (0.38%) at JingHong station, while lightly greater in far future (both 0.21%) than near future (0.13% and 0.17%) at Nong Khai and Kratie stations, along with it keeps the same in near and far future at Pakse station (both 0.17%). Reservoirs show the best effects under SSP585, where they effectively alleviate the FTD probability at all hydrological stations (0.13% to 0.42%). Under SSP126 and SSP245, although the reservoir operation displays poor mitigation effects (-0.33% to 0.38%) at Nong Khai and Pakse stations, it still exhibits nice alleviation at JingHong and Kratie stations, especially under some scenarios (e.g., for JingHong under SSP245 and for Kratie under SSP126). Reservoirs furthermore exhibit superior mitigation capacity against DFAA at JingHong and Kratie compared to Nong Khai and Pakse stations, which coincides with the storage distribution in LMR Basin (Fig. 1c). This indicates that reservoirs not only functions well in flood and drought control

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(Hecht et al., 2019; Hoang et al., 2019; Ly et al., 2023), but excellently respond to unexpected events such as DFAA.

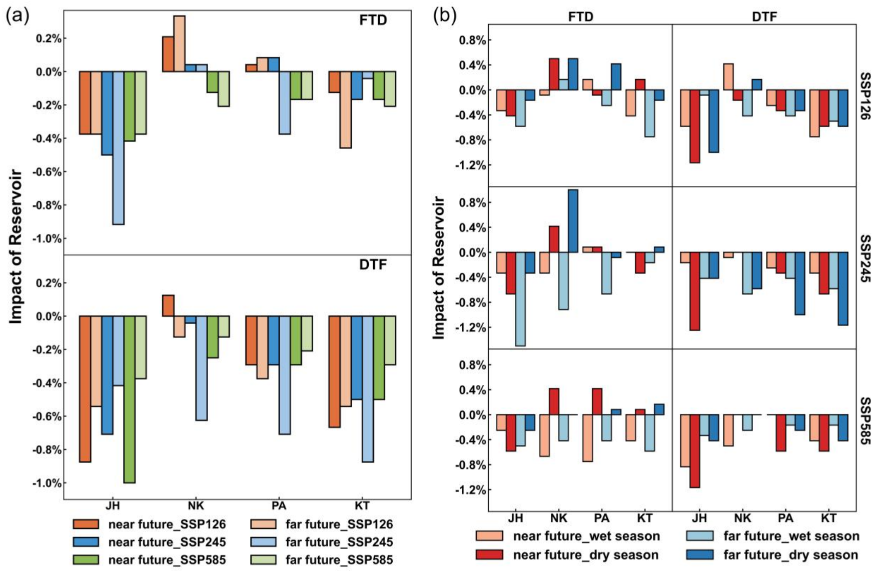

Figure 5: Reservoir impacts on DFAA during near future (2021-2060) and far future (2061-2100) under three SSPs. Note that JH, NK, PA, and KT denote JingHong, Nong Khai, Pakse, and Kratie stations, respectively. (a) The annual reservoir impacts. (b) The seasonal reservoir impacts in wet and dry seasons.

The reduction effect of reservoirs on FTD in wet season (-0.17% to 1.5%) appears to be more remarkable compared to dry season (-1% to 0.67%), especially at Nong Khai, Pakse and Kratie stations (Fig. 5b). Reservoirs basically demonstrate significant reduction effects on FTD in wet season (-0.17% to 0.92%) at these stations, however rise FTD probability somehow for dry season (-1% to 0.33%). Seasonal difference of reservoir mitigation effects on DTF is not as significant as FTD. Reservoirs perform slightly better reduction effects in dry season (-0.17% to 1.25%) on DTF than in wet season (-0.42% to 0.83%), with little difference. Moreover, the reservoir displays superior mitigation in DTF relative to FTD in both dry and wet seasons, which is consistent with the annual DFAA.

DFAA tends to exhibit multiple monthly peaks under natural scenario, implying there are multiple months with higher DFAA probability than their adjacent months. The multiple peaks are more pronounced in DTF than FTD (Fig. 6). As for the monthly DFAA averaged over four mainstream hydrological stations, DTF shows triple peaks in near future under SSP245 and in far future under SSP585, while FTD both exhibits double peaks. The reservoir serves to regulate DFAA by reducing

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peaks and decreasing the number of peaks, where its reduction effect on the number of peaks appears more pronounced in near future and for DTF (Fig. 6). Reservoirs provide robust peak alleviation for far future and FTD, particularly under SSP126 and SSP245, despite their limited contribution in decreasing the number of peaks. Reservoirs meanwhile remarkably reduce DFAA probability in early and middle dry season (i.e., December to April) for both near and far future, cutting the probability for most stations to less than 1% (even 0%). The reservoir furthermore potently shortens DFAA's monthly span from spread out the whole year for natural scenario to concentrating in May to October for dammed scenario (Fig. 6), which enables LMR Basin to centralize relevant policies and practices on DFAA to this period. It therefore facilitates riparian states to integrate resources and concentrate efforts on targeted water resources management to achieve enhanced response and control to DFAA along with secondary hazards.

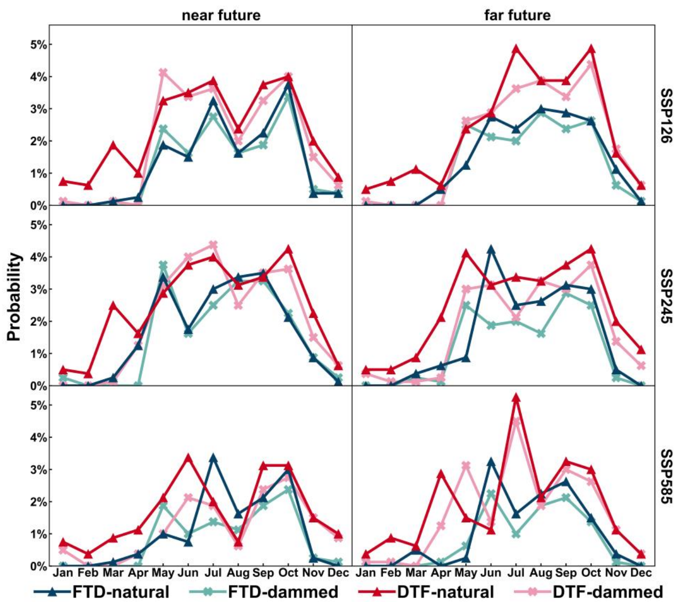

Figure 6: Averaged monthly DFAA probability over four mainstream hydrological stations (i.e., JingHong, Nong Khai, Pakse and Kratie stations) under natural and dammed scenarios for three SSPs during near future (2021-2060) and far future (2061-2100) periods.

4. Discussion

4.1 Different characteristics of DTF and FTD under changing climate

Although flood and drought risks in LMR Basin will decrease respectively in near and far future (Li et

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al., 2021; Hoang et al.,2016; Wang et al., 2017b; Yun et al., 2021a; Yun et al., 2021b), DFAA risk will still increases under SSP126 and SSP245 scenarios (Fig. 4). DTF and FTD exhibit quite different characteristics, in that DTF is more frequent but FTD is more challenging.

The probability of DTF is significantly higher than FTD (Fig. 4a) and rises considerably in near and far future periods (Fig. 4b). However reservoirs well control the DTF probability and significantly reduce the DTF risk in both dry and wet seasons (Fig. 5). This can be attributed to the fact that the DTF's demand for water regulation follows the reservoir scheduling logic, whereby the reservoir releases water to alleviate drought during early DTF, when reservoirs stay at low water level, which exactly satisfies the storage requirements of the sudden flood in late DTF.

Comparatively, although FTD is less probable than DTF, reservoirs poorly control it especially in dry season, which is pertinent to the challenge that reservoirs hardly spare capacity for floods in early FTD whilst ensuring storage for drought during late FTD. FTD tends to occur unexpectedly under the high incidence of DTF, and the current reservoir operation struggles to perfectly control its risk, which lead to extreme challenges in FTD. Fortunately, the probability of FTD however will drop in most areas of LMR Basin in future (Fig. 4).

4.2 Reservoir operation integrated with hydrological forecast

Future DFAA in LMR Basin remains severe (Fig. 4). Reservoirs although provide positive impacts to DFAA under changing climate, yet require improvement in some situations (Fig. 5). This is attributed to the fact that relying on general reservoir operation rules such as SOP only can't fully realize reservoirs' potential (Zhang et al., 2018), which are scheduled with completely unknown incoming flows. The reservoir's ability in respond to DFAA will be further enhanced if being scheduled with known incoming flows. Reservoir scheduling combined with hydrological forecast is a practical approach.

Hydrological forecasting technology excavates the potential of reservoirs, improves their ability to address disasters and optimizes the resilience of LMR Basin system. Hydrological forecast enables the prediction of reservoir inflows and extreme hydrological events at appropriate time scales according to actual requirements (Brunner et al., 2021; Ibrahim et al., 2022), and assists to assess their severity and possible impacts on production and livelihoods in LMR Basin (Kao et al., 2020; Kumar et al., 2023; Prodhan et al., 2022; Hao et al., 2018). Adapting reservoir operations in current and coming periods

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based on runoff and disaster conditions indicated by hydrological forecast enables to optimally utilize the throughput capacity of reservoirs to alleviate flood and following drought closely (take FTD as an example). When the situation is under emergency, for instance the forecast indicates the severe coming disaster, avoiding serious disasters should be the primary purpose of reservoir operations, and appropriate sacrifice of hydropower benefits could be considered to ensure the production and life in LMR Basin.

4.3 Maximize utilization of the resilient storage

The mitigation effect of reservoirs on DFAA risk is closely associated with the storage distribution of mainstream and tributary reservoirs (Figs. 1c and 5). It varies from strong to poor in the order of JingHong, Kratie, Pakse, and Nong Khai, which is exactly the order of total mainstream and tributary reservoir storage from the largest to the smallest. This highlights the capacity of both mainstream and tributary reservoirs in controlling DFAA's risk.

This study only includes the hydropower reservoir in LMR Basin but doesn't cover the other infrastructures that can storage water while can't generate power, such as irrigation reservoirs. The total storage of such infrastructures, however, is considerable. According to MRC, the Mekong Basin contains 1317 irrigation reservoirs, with total storage about 17 billion m^3 (MRC, 2018; LMC and MRC, 2023). This value is higher than total storage in the region between JingHong and Nong Khai stations (around 9.7 billion m^3), and slightly lower than total storage in the region between Nong Khai to Pakse region stations (approximately 22.1 billion m^3), as shown in Fig. 1c.

It is necessary to rationally plan and operate these irrigation reservoirs, such as treating them as the available resilient storage and activating when LMR Basin experiences severe DFAA. Irrigation reservoirs, along with hydropower reservoirs, whose regulation function should be fully utilized to alleviate DFAA impacts and enhance the resilience of basin system.

5. Conclusion

This study adopts CMIP6 meteorological data under three SSP scenarios and five GCMs, and corrects them utilizing MBCn method. Combined hydrological model THREW and the developed reservoir module, it applies R-SDFAI to characterize DFAA, and explores the mitigating role of reservoirs on DFAA under changing climate in LMR Basin. The study periods are organized into history

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(1980-2014), near future (2021-2060) and far future (2061-2100). The main findings are summarized below:

1. Future DFAA trend varies widely in upstream and downstream of LMR Basin, with significant rises in upstream FTD and downstream DTF. While DTF occurs more probable, FTD presents more challenge. Annual and wet season risks of DFAA increase under SSP126 and SSP245 scenarios. The DFAA risk is considerably higher in wet season than dry season.
2. Reservoirs competently reduce year-round risk of DTF and wet season's risk of FTD in LMR Basin, and perform better in regions with larger total storage of mainstream and tributary reservoirs. Moreover, reservoirs contribute markedly to control DFAA's multiple peaks and to shorten its monthly span.
3. Hydrological forecast and resilient storage are able to help smoothly survive DFAA, and could be robust options to address climate change.

This study provides new insights into the mitigating role of reservoirs on DFAA in LMR Basin and contributes to water resource management for riparian countries. DFAA remains severe under climate change and reservoirs do contribute to mitigating it, thus this study calls for information sharing and joint actions among basin countries on the forecast and prevention of DFAA. The joint efforts of LMR Basin states will assist to explore more effective and feasible measures to mitigate impacts of climate change and facilitate the long-term sustainable development.

Author contribution

KZ: Conceptualization; Data curation; Model development; Investigation; Methodology; Validation; Visualization; Writing - original draft; Writing - review & editing. **FT:** Conceptualization; Funding acquisition; Investigation; Methodology; Supervision; Writing - review & editing.

Competing interests

At least one of the (co-)authors is a member of the editorial board of Hydrology and Earth System Sciences.

Data availability

The hydrological data can be accessed and requested from the MRC Data Portal

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(https://portal.mrcmekong.org/home, last access: March 2025). Information related to dams is available on the Mekong Region Futures Institute (MERFI) website (https://www.merfi.org/mekong-region-dams-database, last access: March 2025). The raw CMIP6 data without correction is available at (https://esgf-node.llnl.gov/search/cmip6/, last access: March 2025).

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