

1 **Mitigating the Impact of Increased Drought-Flood**
2 **Abrupt Alteration Events under Climate Change: The**
3 **Role of Reservoirs in the Lancang-Mekong River Basin**

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9 **Abstract.** The Lancang-Mekong River (LMR) Basin is highly vulnerable to extreme hydrological events,
10 including Drought-Flood Abrupt Alteration (DFAA). The efficacy of potential mitigation measures,
11 such as reservoir operations, on DFAA under climate change remains poorly understood. This study
12 investigates these dynamics using five Global Climate Models (GCMs) from the Coupled Model
13 Intercomparison Project Phase 6 (CMIP6). It employs the Revised Short-cycle Drought-Flood Abrupt
14 Alteration Index (R-SDFAI), along with the Tsinghua Representative Elementary Watershed (THREW)
15 model integrated with the developed reservoir module. The findings reveal that DFAA in the LMR Basin
16 is primarily dominated by DTF (drought to flood), with probabilities of DTF exceeding those of FTD
17 (flood to drought) at mild, moderate, and severe intensity levels. The increase in DTF probability for
18 future periods is also significantly higher than that of FTD. Mild DTF and mild FTD account for 58% to
19 90% and 75% to 100% of their total probability in the future, making the mild-intensity events the most
20 frequent DFAA. Reservoirs play a significant role in reducing DTF risks during both dry and wet seasons,
21 though their effectiveness in controlling FTD risks, particularly during the dry season, is relatively
22 weaker. Furthermore, there is a positive correlation between the reservoir's capacity to mitigate total
23 DFAA risk and its total storage. Reservoirs display a stronger ability to regulate high-intensity FTD and
24 high-frequency DTF events, and significantly reduce the monthly duration of DFAA. These insights
25 provide valuable guidance for the effective management of water resources cooperatives across the LMR
26 Basin.

27 **Keywords.** Drought-Flood Abrupt Alteration; Climate change; Reservoir operation; Lancang-Mekong
28 River Basin.

29 **1. Introduction**

30 Flood and drought are two of the most frequent natural disasters in the world (Adikari and Yoshitani,
31 2009; ADREM et al., 2024). Drought-Flood Abrupt Alternation (DFAA), which is defined as the rapid
32 transition between flood and drought conditions within a region (Xiong and Yang, 2025), has received
33 growing attention in recent years (Chen et al., 2025; Wu et al., 2023; Zhang et al., 2012; Shan et al., 2018;
34 Song et al., 2023). DFAA specifically consists of two types of rapid transition events: (1) drought to flood
35 (DTF), where conditions shift quickly from drought to flood, and (2) flood to drought (FTD), where
36 conditions rapidly change from flood to drought. Hazards arising from DFAA are more significant than
37 those from floods and droughts. DFAA not only alters soil conditions and increases the potential for
38 exceeding water quality standards (Bai et al., 2023; Yang et al., 2019) but also challenges food security
39 and seriously affects agricultural production. Furthermore, DFAA events, particularly DTF events, are
40 prone to triggering severe secondary natural hazards, primarily including flash floods, landslides, and
41 mudslides (Wang et al., 2023).

42 It has been observed that the intensity and frequency of DFAA events demonstrate a global increasing
43 trend (Yang et al., 2022; Chen et al., 2024). However, notable regional differences exist. Shan et al. (2018)
44 observed that the scope of DFAA events in the Yangtze River mid-lower reaches has expanded since the
45 1960s, with both frequency and intensity increasing annually. Zhang et al. (2012) found that although
46 droughts and floods have increased in the Huai River Basin, DFAA events have become less frequent.
47 Looking ahead, Zhao et al. (2022) projected that the Han River Basin will experience an upward trend in
48 both DFAA frequency and intensity, whereas Yang et al. (2019) reported a projected decline in the
49 frequency of DFAA events in the Hetao region.

50 The Lancang-Mekong River (LMR), as a significant international river in Southeast Asia, profoundly
51 affects key sectors such as hydropower, agriculture, fisheries, and transport (Morovati et al., 2024). At
52 the same time, the LMR Basin is a high-incidence area for floods and droughts (Liu et al., 2020; MRC,
53 2020). Notably, wet-season droughts account for about 40% of annual droughts (Tian et al., 2020), while
54 the region is also prone to large floods during the dry season (e.g., May 2006, May 2007, December 2016)
55 (Tellman et al., 2021). The existence of these wet-season droughts and dry-season floods establishes the
56 necessary conditions for DFAA in the LMR Basin.

57 Continued global warming is expected to further intensify both extreme wet and dry climate patterns

58 (IPCC, 2023), contributing to increased vulnerability to DFAA in the future (Yang et al., 2022; Wang et
59 al., 2023; Chen et al., 2025). There is a strong tendency toward more intense floods and droughts in
60 Southeast Asia (IPCC WG1, 2021) and specifically in the LMR Basin (Wang et al., 2021; Li et al., 2021;
61 Dong et al., 2022; Hoang et al., 2016). This heightens concerns about DFAA patterns in the LMR Basin,
62 emphasizing the need for improved water security, sustainable management, and early disaster
63 forecasting and prevention systems.

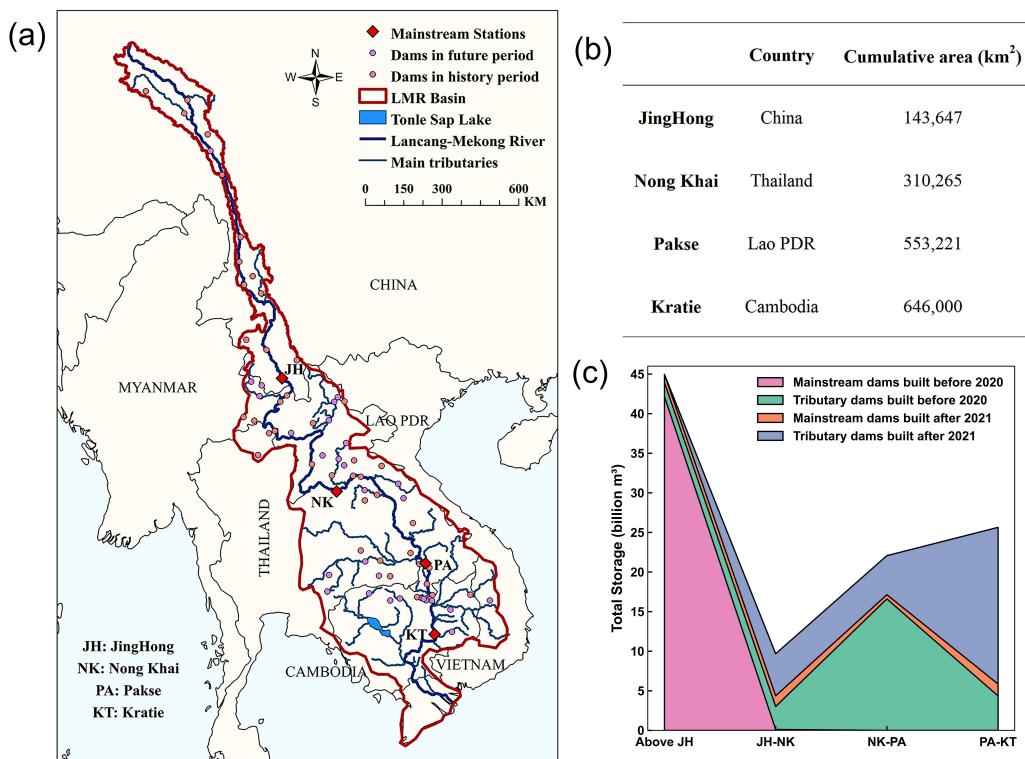
64 The hydrological regime of the LMR Basin is shaped mainly by climate change and human activities
65 (LMC and MRC, 2023). Despite the severe impacts of climate change, human activities such as reservoir
66 operation can help adapt the hydrological regime to these changes (Zhang et al., 2023; Khadka et al.,
67 2023; Sridhar et al., 2019; Lu et al., 2014; Gunawardana et al., 2021). Researches highlight that reservoirs
68 play a crucial role in reducing flood damage during the wet season and in minimizing low-flow
69 occurrences (Arias et al., 2014; Räsänen et al., 2012; Dang and Pokhrel, 2024). To evaluate reservoir
70 impacts under the changing climate, integration of a reservoir module within hydrological models is a
71 widely adopted practice. For example, Wang et al. (2017b) demonstrated that reservoir operation can
72 reduce flood intensity and frequency, while Yun et al. (2021a; 2021b) showed that careful reservoir
73 management can relieve both extreme drought and wet events, though with some trade-offs in
74 hydroelectric benefits. Collectively, these studies indicate that reservoirs offer practical adaptation
75 solutions to address climate change impacts.

76 It is essential to consider how human activities, especially reservoir operations, can help manage DFAA
77 under climate change. This consideration supports effective water resource management and the
78 sustainable development of the basin system. However, little research to date has focused on this aspect
79 for the LMR Basin. The statistics, reports, and studies on DFAA in the LMR Basin remain scarce,
80 particularly concerning the mitigating role of reservoirs under the changing climate. In response, this
81 study develops a reservoir module for hydrological modeling, examines the trends of DFAA in the LMR
82 Basin under climate change, and assesses how reservoirs can help basin states adapt to changing
83 conditions. This work aims to advance knowledge on DFAA and support regional water resources
84 management and sustainability.

85 **2. Methodology**

86 **2.1 Study area**

87 The LMR originates from the Tibetan Plateau in China and flows through China, Myanmar, Laos,
 88 Thailand, Cambodia, and Vietnam before entering the South China Sea at the Mekong Delta. The LMR
 89 is approximately 4900 km long with a basin area of 812,400 km² (He, 1995). Its annual runoff is about
 90 446 billion m³ (MRC, 2023). The LMR Basin is characterized by steep slopes and rapid flows in the
 91 upstream. The downstream features shallow slopes and slow, mixed flows. The wet and dry seasons in
 92 the LMR Basin extend from June to November and from December to May, respectively (LMC and MRC,
 93 2023). These are mainly influenced by the southwestern and northeastern monsoons. The distribution of
 94 the hydrology system and mainstream hydrological stations in the LMR Basin is detailed in Fig. 1a.



95
 96 **Figure 1: Hydrology of the LMR Basin. (a) Map of rivers and reservoirs, (b) Information on four main**
 97 **hydrological stations, and (c) distribution of reservoir storage. Here, JH, NK, PA, and KT denote JingHong,**
 98 **Nong Khai, Pakse, and Kratie stations, respectively.**

99 The LMR Basin nourishes approximately 65 million people (Sabo et al., 2017; Luo et al., 2023). The
 100 basin states rely on the river system to develop economic industries, including capture fisheries, irrigation
 101 agriculture, and hydropower. The LMR Basin has the largest freshwater capture fishery in the world
 102 (MRC, 2010; MRC, 2019). Its irrigation area is estimated at around 4.3 million hectares (Do et al., 2020),
 103 with the Mekong Delta regarded as Southeast Asia's food basket. The LMR Basin is one of the most

104 active regions for hydropower in the world (MRC, 2019; Williams, 2019). It harbors about 235,000
105 GWhyr⁻¹ of hydroelectric potential in its mainstream and tributaries (Do et al., 2020; Schmitt et al., 2018).
106 The LMR Basin is also heavily impacted by floods and droughts. During the past two decades, the LMR
107 Basin has experienced several severe droughts (2004-2005, 2009-2010, 2015-2016, and 2019-2020) and
108 floods (Liu et al., 2020; Tian et al., 2020; MRC, 2020). These disasters affect crop cultivation and
109 fisheries harvesting, leading to the loss of property and lives in riparian countries. In 2013 and 2018,
110 floods heavily affected the lower basin, specifically Cambodia, Vietnam, Laos, and Thailand. These
111 floods covered 22.3 and 6.47 thousand km², respectively (Tellman et al., 2021).

112 **2.2 Data collection**

113 This study utilizes CMIP6 (Sixth Phase of Coupled Model Inter-comparison Project) data as the
114 meteorological input to analyze DFAA. Three SSP (Shared Socioeconomic Pathways) scenarios, namely
115 SSP1-2.6, SSP2-4.5, and SSP5-8.5, are considered to characterize the low-, medium-, and high-emission
116 scenarios, respectively. Five GCMs (Global Climate Models) with wide utilization and proven
117 performance in the LMR Basin are applied in this study (Li et al., 2021; Yun et al., 2021a; Yun et al.,
118 2021b), i.e., GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL.
119 The detailed information for these five GCMs is shown in Table 1 (Eyring et al., 2016; Gidden et al.,
120 2019; Cui et al., 2023). CMIP6 data span from 1980 to 2100. This study accordingly considers three
121 research periods: the history period from 1980 to 2014 (consistent with CMIP6), the near future period
122 from 2021 to 2060, and the far future period from 2061 to 2100.

123 In this study, the daily observed runoff data at four major mainstream hydrological stations from 1980 to
124 2020 are used to calibrate and validate the hydrological model. These data are derived from the China
125 Meteorological Administration (CMA) and the Mekong River Commission (MRC). The hydrological
126 stations from upstream to downstream are sequentially JingHong, Nong Khai, Pakse, and Kratie, whose
127 locations and basic information are shown in Figs. 1a and 1b. This study uses the ERA5_Land data as
128 the meteorological input for calibrating and validating the hydrological model, and as the correction
129 dataset for correcting the raw CMIP6 data. ERA5_Land data cover the period from 1980 to 2020, with a
130 spatial resolution of 0.1°, and contain precipitation, temperature, and potential evapotranspiration. Soil
131 data are obtained from the Global Soil Database (GSD) provided by the Food and Agriculture
132 Organization of the United Nations (FAO) with a spatial resolution of 10 km x 10 km. Normalized

133 Vegetation Index (NDVI), Leaf Area Index (LAI), and Snow Cover data are obtained from MODIS
 134 (Moderate-resolution Imaging Spectroradiometer) with a spatial resolution of 500 m x 500 m and a
 135 temporal resolution of 16 days.

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

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

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°

142 **2.3 Bias correction method for CMIP6 data**

143 The raw CMIP6 data require correction for more accurate modelling (Hoang et al., 2016; Mishra et al.,
 144 2020; Sun et al., 2023). The uncorrected raw CMIP6 data misestimate the temperature and precipitation
 145 in the LMR Basin, especially overestimating the precipitation (Cui et al., 2023; Lange, 2019; Lange,
 146 2021). ERA5_Land data are used as correction data in this study to address bias in raw CMIP6 data.
 147 This study interpolates the data from the five GCMs of CMIP6, which have different spatial resolutions,
 148 to 0.1° (consistent with ERA5_Land) using the bilinear interpolation spatial resolution method. The
 149 interpolated CMIP6 data are bias-corrected for each GCM according to an N-dimensional probability
 150 density function transform of the multivariate bias correction approach (abbreviated as MBCn) (Cannon,
 151 2016; Cannon, 2018). The MBCn method is trained based on the difference between precipitation and
 152 temperature data from ERA5_Land and CMIP6 over the history period (1980-2014), and then applied to
 153 the future period (i.e., 2021-2100) to correct the CMIP6 data for each GCM.

154 The MBCn method considers the multivariate dependency structure of meteorological data and enables
 155 the simultaneous correction of temperature and precipitation data. Random orthogonal rotation and
 156 quantile delta mapping are the two most critical formulas of the MBCn method (Cannon, 2018), as
 157 illustrated in Eqs. (1) and (2).

$$158 \quad \begin{cases} \tilde{\mathbf{X}}_T^{[l]} = \mathbf{X}_T^{[l]} \mathbf{R}^{[l]} \\ \tilde{\mathbf{X}}_S^{[l]} = \mathbf{X}_S^{[l]} \mathbf{R}^{[l]} \\ \tilde{\mathbf{X}}_P^{[l]} = \mathbf{X}_P^{[l]} \mathbf{R}^{[l]} \end{cases} \quad (1)$$

159 Eq. (1) displays the process of random orthogonal rotation. It outlines the process of transforming
 160 historical observations $\mathbf{X}_T^{[l]}$, historical climate model simulations $\mathbf{X}_S^{[l]}$, and climate model projections
 161 $\mathbf{X}_P^{[l]}$ using a random orthogonal rotation matrix $\mathbf{R}^{[l]}$ during the l -th iteration. The rotated data are
 162 represented as $\tilde{\mathbf{X}}_T^{[l]}$, $\tilde{\mathbf{X}}_S^{[l]}$, and $\tilde{\mathbf{X}}_P^{[l]}$. This procedure is pivotal for MBCn's multivariate joint distribution
 163 correction, as it transforms the original variable space into new random orientations. In contrast to
 164 conventional univariate correction approaches, MBCn employs a random orthogonal matrix to mix
 165 variables, thereby breaking their independence.

$$166 \quad \begin{cases} \Delta^{(n)[l]}(i) = \tilde{x}_P^{(n)[l]}(i) - F_S^{(n)[l]-1}(F_P^{(n)[l]}(\tilde{x}_P^{(n)[l]}(i))) \\ \hat{x}_P^{(n)[l]}(i) = F_T^{(n)[l]-1}(F_P^{(n)[l]}(\tilde{x}_P^{(n)[l]}(i))) + \Delta^{(n)[l]}(i) \end{cases} \quad (2)$$

167 Eq. (2) exhibits the quantile delta mapping, which defines how quantile delta mapping is applied to the
 168 n -th dimension of the rotated climate model projection data $\tilde{x}_P^{(n)[l]}(i)$ within the rotated space of the l -
 169 th iteration. Here, $\Delta^{(n)[l]}(i)$ represents the quantile difference between the historical climate model
 170 simulations and climate model projections in the l -th iteration and the n -th dimension. $F_P^{(n)[l]}$ denotes
 171 the empirical cumulative distribution function for the rotated climate model projection data in the n -th
 172 dimension. $F_T^{(n)[l]-1}$ and $F_S^{(n)[l]-1}$ denote inverse Functions of the empirical cumulative distribution
 173 functions for the rotated historical observation data and historical climate model simulation data in the
 174 n -th dimension. This step preserves the trend of the climate model projection data throughout the
 175 correction process. The number of iterations is typically set to 10-30.

176 The MBCn algorithm performs multivariate joint distribution bias correction by iteratively applying
 177 random orthogonal rotation and quantile delta mapping, while preserving the projected signals in the
 178 climate model. The rotation operation breaks dependencies between variables, enabling the quantile delta
 179 mapping of a single variable to indirectly adjust multivariate correlations. The quantile delta mapping
 180 ensures the transmission of absolute or relative trends by computing quantile differences between the

181 historical and projected periods of the climate model. The MBCn method has been reported to increase
182 correction precision and accuracy compared to univariate and other multivariate bias correction
183 algorithms (Cannon, 2018).

184 In addition, this study utilized the method proposed by Van Pelt et al. (2009) to compute daily potential
185 evapotranspiration data for five GCMs under three SSP scenarios, based on daily temperature. The
186 computational approach is outlined in Eq. (3).

187
$$PET = [1 + \alpha_0(T - \bar{T}_0)]\bar{PET}_0 \quad (3)$$

188 Where, \bar{T}_0 and \bar{PET}_0 correspond to the daily air temperature ($^{\circ}\text{C}$) and daily potential
189 evapotranspiration (mm day^{-1}) in the history period sourced from ERA5_Land dataset. T signifies the
190 corrected daily air temperature ($^{\circ}\text{C}$) from CMIP6 dataset. The parameter α_0 is determined by the
191 relationship between daily potential evapotranspiration and daily temperature in ERA5_Land data during
192 the history period.

193 **2.4 Hydrological model coupled with reservoir module**

194 The THREW (Tsinghua Representative Elementary Watershed) hydrological model is applied in this
195 study for runoff simulation. It utilizes the Representative Elementary Watershed (REW) approach for
196 spatial division, and further subdivides the REW into eight distinct hydrological zones: vegetated zone,
197 bare soil zone, glacier covered zone, snow covered zone, sub-stream-network zone, main channel reach,
198 saturated zone, and unsaturated zone (Tian et al., 2006; Mou et al., 2008).

199 The model is built upon scale-coordinated equilibrium equations, geometrical relationships, and
200 constitutive relationships, and enables comprehensive simulation of complex hydrological processes
201 from mountain to ocean. The fundamental balance equations in the THREW model are listed in Eqs. (4)
202 to (6).

203
$$\frac{d}{dt}(\bar{\rho}_\alpha^j \epsilon_\alpha^j y^j \omega^j) = \sum_P e_\alpha^{jP} + \sum_{\beta \neq \alpha} e_{\alpha\beta}^j \quad (4)$$

204 Eq. (4) demonstrates the general form of the mass conservation equation at the REW scale. $\frac{d}{dt}$ denotes
205 the time derivative. $\bar{\rho}_\alpha^j$ refers to the time-averaged density of phase α in sub-region j , in $\text{kg}\cdot\text{m}^{-3}$. ϵ_α^j
206 means the volume fraction of phase α within sub-region j . y^j indicates the time-averaged thickness of
207 sub-region j , in m. ω^j means the time-averaged fraction of REW horizontal area occupied by sub-region
208 j . e_α^{jP} denotes the net mass exchange flux of phase α in sub-region j through interface P (e.g., with

209 atmosphere, groundwater, neighboring REWs), in $\text{kg}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$, where a positive value indicates the inflow
 210 to sub-region j . $e_{\alpha\beta}^j$ refers to the phase transition rate between phase α and phase β within sub-region
 211 j , in $\text{kg}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$, where a positive value indicates phase α gains mass from phase β . Sub-region here
 212 refers to the eight zones within each REW.

$$213 \quad (\overline{\rho_\alpha^j} \epsilon_\alpha^j y^j \omega^j) \frac{d\overline{v_\alpha^j}}{dt} = \overline{g_\alpha^j} \overline{\rho_\alpha^j} \epsilon_\alpha^j y^j \omega^j + \sum_P T_\alpha^{jP} + \sum_{\beta \neq \alpha} T_{\alpha\beta}^j \quad (5)$$

214 Eq. (5) presents the general form of the momentum conservation equation at the REW scale. $\overline{v_\alpha^j}$
 215 indicates the time-averaged velocity vector of phase α in sub-region j , in $\text{m}\cdot\text{s}^{-1}$. $\overline{g_\alpha^j}$ denotes the time-
 216 averaged gravity vector of phase α in sub-region j , in $\text{m}\cdot\text{s}^{-2}$. T_α^{jP} means the force vector (pressure,
 217 friction, seepage) exerted on phase α in sub-region j by interface P , in $\text{N}\cdot\text{s}^{-2}$, representing the
 218 momentum exchange. $T_{\alpha\beta}^j$ refers to the interfacial force vector between phase α and phase β within
 219 sub-region j , in $\text{N}\cdot\text{s}^{-2}$, including drag and capillarity.

$$220 \quad (\epsilon_\alpha^j y^j \omega^j c_\alpha^j) \frac{d\overline{\theta_\alpha^j}}{dt} = \overline{h_\alpha^j} \overline{\rho_\alpha^j} \epsilon_\alpha^j y^j \omega^j + \sum_P Q_\alpha^{jP} + \sum_{\beta \neq \alpha} Q_{\alpha\beta}^j \quad (6)$$

221 Eq. (6) exhibits the general form of the heat conservation equation at the REW scale. c_α^j means the
 222 specific heat capacity (constant volume) of phase α in sub-region j , in $\text{J}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$. $\overline{\theta_\alpha^j}$ refers to the time-
 223 averaged temperature of phase α in sub-region j , in K . $\overline{h_\alpha^j}$ denotes the heat generation rate per unit mass
 224 within phase α in sub-region j , in $\text{W}\cdot\text{kg}^{-1}$ (e.g., radioactive decay, negligible usually). Q_α^{jP} indicates
 225 the heat exchange rate between phase α in sub-region j and its environment via interface P , in $\text{W}\cdot\text{m}^{-2}$,
 226 with the positive value representing the heat gained by phase α in sub-basin j . $Q_{\alpha\beta}^j$ refers to the heat
 227 exchange rate between phase α and phase β within sub-region j , in $\text{W}\cdot\text{m}^{-2}$, with a positive value
 228 indicating that heat is gained by phase α .

229 The THREW model employs an automatic calibration procedure to calibrate hydrological parameters
 230 through parallel computation (Nan et al., 2021). The calibration period of the THREW model in the LMR
 231 Basin is from 2000 to 2009, and the validation period is from 2010 to 2020. The calibration process
 232 involves nine hydrological parameters. A compilation of their explanations and permissible value ranges
 233 is given in Table 2. The Nash-Sutcliffe efficiency coefficient (NSE) indicator is adopted to calibrate the
 234 objective function and evaluate simulation effectiveness at the daily scale, which is calculated according
 235 to Eq. (7). The THREW model has been successfully applied to a number of basins with various climate
 236 characteristics worldwide (Tian et al., 2012; Lu et al., 2021; Morovati et al., 2023; Cui et al., 2023; Zhang

237 et al., 2023).

238
$$NSE = 1 - \frac{\sum_{num=1}^N (Q_{obs}^{num} - Q_{sim}^{num})^2}{\sum_{num=1}^N (Q_{obs}^{num} - \bar{Q}_{obs})^2} \quad (7)$$

239 Where, Q_{obs}^{num} is the daily observed runoff, Q_{sim}^{num} is the daily simulated runoff, \bar{Q}_{obs} is the average of
240 observed runoff, and N is the total number of days.

241 **Table 2: Calibrated hydrological parameters and their ranges.**

Parameter	Explanation	Range
kv	Fraction of potential transpiration rate over potential evaporation	0-10
nt	Roughness of slope	0-2
KKA	Exponential coefficient in subsurface runoff calculations	0-100
nr	Roughness of river channel	0-1
KKD	Linear coefficient in subsurface runoff calculation	0-1
B	Shape coefficient	0-1
WM	Average water storage capacity (m)	0-5
K	Storage factor in Muskingum Method	0-1
X	Flow ratio factor in Muskingum Method	0-0.5

242 This study extends the THREW model by developing and integrating a reservoir management module.
243 This integration allows the expanded THREW model to use detailed information on 122 reservoirs in the
244 LMR Basin, with operational years ranging from 1965 to 2035. By specifying whether the module is
245 active, the model can simulate either natural runoff (without considering reservoirs) or dammed runoff
246 (with reservoirs included). This setup ensures a seamless interaction between the core model and the
247 reservoir operations framework.

248 Reservoir operation follows consistent rules across time and space, with each reservoir starting operation
249 according to its operational year. Strategies are adapted in response to inflow fluctuations and
250 administered on a daily scale. Each reservoir is assigned based on location. Cumulative multi-year sub-
251 basin storage is calculated as input for the reservoir module, which operates in two phases: initial and
252 normal. The normal phase is divided into general and emergency cases, both using the same operation
253 rules but differing constraints; the emergency case allows more flexibility. The module's flowchart is
254 illustrated in Fig. 2.

255 If a REW's cumulative multi-year storage changes within a year, it signals the start of a new reservoir's
256 operation, which follows initial phase rules. During the initial phase, the outlet flow matches the inlet if
257 it is below the minimum discharge constraint; otherwise, it meets the minimum discharge constraint. The

258 rules for the initial phase are described as Eqs. (8) to (9). Storage and discharge constraints are defined
 259 in Eqs. (10) to (11) (Tennant, 1976; Yun et al., 2020). The initial phase ends when reservoir storage
 260 exceeds the minimum constraint (Eq. (12)), then transitions to the normal phase.

261
$$Q_{out} = \begin{cases} Q_{in}, & Q_{in} < Q_{min} \\ Q_{min}, & Q_{in} \geq Q_{min} \end{cases} \quad (8)$$

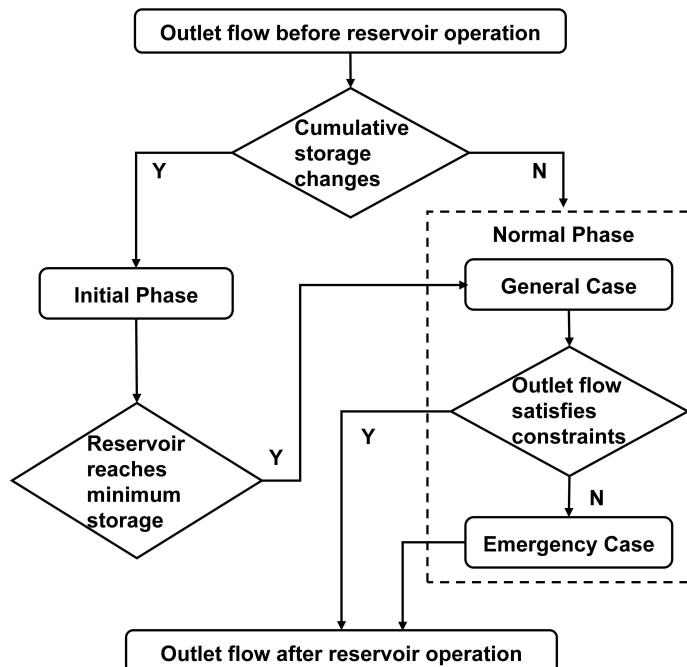
262
$$S_t = S_{t-1} + Q_{in} - Q_{out} \quad (9)$$

263
$$S_{min} = 0.2 \times S_{total} \quad (10)$$

264
$$Q_{min} = 0.6 \times Q_{ave} \quad (11)$$

265
$$S_t \geq S_{min} \quad (12)$$

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



269

270 **Figure 2: Flowchart of the constructed reservoir module.**

271 The scheduling rule for the normal phase is the improved Standard Operation Policy hedging model
 272 (SOP) (Wang et al., 2017a; Morris and Fan, 1998), as depicted in Eq. (9) and Eqs. (13) to (16). The SOP
 273 operating policy is proven to effectively capture floods and droughts under reservoir regulation (Wang et
 274 al., 2017a; Yun et al., 2020; 2021a; 2021b). Under the premise of water balance (Eq. (9)), constraints for

275 annual storage (Eq. (13)), outlet flow (Eq. (14)), wet season storage (Eq. (15)), and dry season storage
 276 (Eq. (16)) are considered separately, where priority is given to the annual storage constraint (Eq. (13)).

277 $S_{min} \leq S_t \leq S_{max}$ (13)

278 $Q_{min} \leq Q_{out} \leq Q_{max}$ (14)

279 $\min|S_c - S_t|, month = 6,7,8,9,10,11$ (15)

280 $\min|S_n - S_t|, month = 12,1,2,3,4,5$ (16)

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

284 When in the normal phase, the reservoir first applies general case constraints (Eqs. (17) to (22)). If outlet
 285 flow is not fully satisfied (Eq. (14)), constraints switch to the emergency case, and the reservoir is
 286 rescheduled. Eq. (23) signals an emergency case start, which provides more flexible flow limits to avoid
 287 extremes. Emergency case constraints are in Eqs. (24) to (25).

288 $Q_{max} = 2 \times Q_{ave}$ (17)

289 $Q_{min} = 0.6 \times Q_{ave}$ (18)

290 $S_c = S_{min} \times 1.2$ (19)

291 $S_n = S_{max} \times 0.8$ (20)

292 $S_{min} = 0.2 \times S_{total}$ (21)

293 $S_{max} = \begin{cases} 0.8 \times S_{total}, month = 6,7,8,9,10,11 \\ 1 \times S_{total}, month = 12,1,2,3,4,5 \end{cases}$ (22)

294 $Q_{min} \leq Q_{out}' \leq Q_{max}$ (23)

295 $Q_{min} = 0.3 \times Q_{ave}$ (24)

296 $S_{max} = 0.8 \times S_{total}$ (25)

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

298 **2.5 Indicator for DFAA**

299 It is common practice to quantify DFAA incidents via indices. Long-cycle droughts-floods abrupt

300 alternation index (LDFAI), proposed by Wu et al. (2006), quantitatively characterizes long-term DFAA
 301 during the wet season and has been widely adopted (Ren et al., 2023; Shi et al., 2021; Yang et al., 2022;
 302 Yang et al., 2019). Building on this, Zhang et al. (2012) introduced the one-month interval SDFAI (short-
 303 cycle droughts-floods abrupt alternation index), extending its application from precipitation to runoff and
 304 characterizing short-term DFAA. SDFAI has since been applied in fields such as hydrology, meteorology,
 305 ecology, and agriculture (Zhao et al., 2022; Lei et al., 2022; Yang et al., 2019; Zhang et al., 2019).
 306 Song et al. (2023) proposed the Revised Short-cycle Drought-Flood Abrupt Alteration Index (R-SDFAI),
 307 which extends the LDFAI and SDFAI time frame from only the flood season to the entire year, facilitating
 308 multi-year DFAA analysis. R-SDFAI also addresses issues of over-identification, under-identification,
 309 and misrepresentation of DFAA severity found in SDFAI. Therefore, this study uses R-SDFAI for DFAA
 310 analysis, with the formulas outlined in Eqs. (26) to (31) (Song et al., 2023).

$$311 \quad F_1 = S_{i+1} - S_i \quad (26)$$

$$312 \quad F_2 = |S_{i+1}| + |S_i| \quad (27)$$

$$313 \quad F = \left| \frac{F_1}{F_2} \right|^{|S_{i+1}| + |S_i|} \quad (28)$$

$$314 \quad I = F \times \min(|S_{i+1}|, |S_i|) \quad (29)$$

$$315 \quad I' = \left(\frac{I}{0.5} \right)^{\frac{\max(|S_{i+1}|, |S_i|)^2}{|F_1| + F_2}} \times \frac{\frac{\max(|S_{i+1}|, |S_i|)}{|F_1| + F_2}}{+ \frac{\min(|S_{i+1}|, |S_i|)}{|F_1| + F_2}}_2 \quad (30)$$

$$316 \quad R - SDFAI = sign(F_1) \times \left(\frac{I'}{I'_{0.5}} \times \frac{I}{0.5} \right)^{\frac{\max(|S_{i+1}|, |S_i|)}{|F_1| + F_2} [1 - \frac{\max(|S_{i+1}|, |S_i|)}{|F_1| + F_2}]} \quad (31)$$

317 Where, S_i refers to the SRI in month i , $F1$ denotes the intensity of DFAA, $F2$ denotes the absolute
 318 intensity of drought and flood, and F is a weighting factor between 0 and 1. $I'_{0.5}$ refers to I' when
 319 $I=0.5$.

320 The calculation process of the SRI indicator utilized in this work is elucidated in Eqs. (32) to (37). The
 321 runoff simulated by the THREW model for the LMR Basin conforms to a Gamma distribution, as detailed
 322 in Appendix 1 of the Supplementary File. Hence, the Gamma distribution is adopted to derive the SRI
 323 index. Eq. (32) gives the probability density function that satisfies the Gamma distribution for runoff x
 324 at a given time period.

$$325 \quad g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}}, x > 0 \quad (32)$$

326 Where, $\alpha > 0$ and $\beta > 0$ are respectively the shape and scale parameters. $\hat{\alpha}$ and $\hat{\beta}$ are the optimal
 327 values of α and β , obtained according to the maximum likelihood estimation method, as illustrated in
 328 Eqs. (33) to (35). $\Gamma(\alpha)$ is the gamma function, as given in Eq. (36).

$$329 \quad \hat{\alpha} = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}} \right) \quad (33)$$

$$330 \quad \hat{\beta} = \frac{\bar{x}}{\hat{\alpha}} \quad (34)$$

$$331 \quad A = \ln(\bar{x}) - \frac{\sum \ln(x_i)}{num} \quad (35)$$

$$332 \quad \Gamma(\alpha) = \int_0^{\infty} y^{\alpha-1} e^{-y} dy \quad (36)$$

333 Where, x_i is the sample of runoff sequence, \bar{x} is the average runoff, and num is the length of the
 334 runoff sequence.

335 Then the cumulative probability of runoff x is illustrated in Eq. (37).

$$336 \quad G(x) = \int_0^x g(x) dx = \frac{1}{\hat{\beta} \hat{\alpha} \Gamma(\hat{\alpha})} \int_0^x x^{\hat{\alpha}-1} e^{-\frac{x}{\hat{\beta}}} dx, x > 0 \quad (37)$$

337 **Table 3: The evaluation criteria and intensity classification for DFAA events.**

Event	Intensity	Classification
DTF	Mild	$1 \leq R\text{-SDFAI} < 1.44$
	Moderate	$1.44 \leq R\text{-SDFAI} < 1.88$
	Severe	$R\text{-SDFAI} \geq 1.88$
FTD	Mild	$-1.44 < R\text{-SDFAI} \leq -1$
	Moderate	$-1.88 < R\text{-SDFAI} \leq -1.44$
	Severe	$R\text{-SDFAI} \leq -1.88$

338 The R-SDFAI index identifies DFAA events with a threshold of ± 1 (Song et al., 2023), and further
 339 categorizes DFAA events into three intensity levels—mild, moderate, and severe—using thresholds of
 340 ± 1 , ± 1.44 , and ± 1.88 , as demonstrated in Table 3. This classification follows the criteria proposed by
 341 Song et al. (2023). The underlying rationale involves using ± 0.5 , ± 1 , and ± 1.5 as thresholds for the
 342 SRI index to categorize extreme hydrological events into mild, moderate, and severe droughts and floods
 343 (positive values indicate flood, while negative values indicate drought). The R-SDFAI index values of
 344 ± 1 , ± 1.44 , and ± 1.88 are calculated through the transitions between mild drought and mild flood,
 345 moderate drought and moderate flood, and severe drought and severe flood. These thresholds serve as
 346 the classification criteria for mild, moderate, and severe DFAA events. For a more detailed explanation

347 of this classification standard, please refer to Song et al. (2023). In this study, the frequency of DFAA
 348 events is represented by their occurrence probabilities during history, near future, and far future periods,
 349 while the intensity of DFAA is assessed through the probability of different intensity events.

350 **2.6 Scenario Setting**

351 This study examines two scenarios: dammed (with reservoir operations) and natural (without reservoir
 352 operations). Meteorological data from five GCMs under three SSPs are downscaled to the REW scale
 353 and used as input for the THREW model. The model, with the reservoir module, simulates runoff at key
 354 hydrological stations for the history period (1980-2014), the near future (2021-2060), and the far future
 355 (2061-2100). Both scenarios—with and without reservoir management—are examined. The R-SDFAI
 356 indicator evaluates DFAA event probabilities for each period and for each scenario, using runoff
 357 simulated by 5 GCMs and 3 SSPs.

358 This study adopts the difference in DFAA's probability between the natural scenario (without reservoir
 359 operations) and the dammed scenario (with reservoir operations) to capture the reservoir's impact, as
 360 shown in Eq. (38).

$$361 P_{Impact\ of\ Reservoirs,i,e} = P_{Dammed,i,e} - P_{Natural,i,e} \quad (38)$$

362 Where $P_{Impact\ of\ Reservoirs,i,e}$ represents the impact of reservoirs on the probability of event e in period
 363 i . $P_{Natural,i,e}$ denotes the probability of event e under the natural scenario in period i , while $P_{Dammed,i,e}$
 364 denotes the probability of event e under the dammed scenario in period i . Period i refers to near future or
 365 far future. Event e indicates DTF, FTD, or DFAA.

366 Eqs. (39) and (40) give the definitions of $P_{Natural,i,e}$ and $P_{Dammed,i,e}$ described above.

$$367 P_{Natural,i,e} = \frac{M_{Natural,i,e}}{TM_i} \quad (39)$$

$$368 P_{Dammed,i,e} = \frac{M_{Dammed,i,e}}{TM_i} \quad (40)$$

369 Where $M_{Natural,i,e}$ denotes the number of months in which event e occurs in period i under the natural
 370 scenario. $M_{Dammed,i,e}$ denotes the number of months occurred event e in period i under the dammed
 371 scenario. TM_i refers to the total number of months in period i . Period i refers to near future or far future.
 372 Event e indicates the DTF, FTD, or DFAA.

373 As each GCM possesses a unique structure and assumptions, projections of climate change by a single
374 GCM inherently possess uncertainties, which in turn introduce uncertainties in the simulation of
375 hydrological outcomes (Kingston et al., 2011; Thompson et al., 2014). Thus, averaging across multiple
376 GCMs is a crucial approach, as it minimizes model biases, eliminates outliers, reduces uncertainties, and
377 ensures more robust and universally applicable outcomes (Lauri et al., 2012; Hoang et al., 2016; Hecht
378 et al., 2019; Wang et al., 2024; Yun et al., 2021b). This method has been extensively employed in prior
379 studies (Dong et al., 2022; Li et al., 2021; Wang et al., 2022; Yun et al., 2021a). Therefore, this research
380 determines the average DFAA probability from five GCMs to lessen the uncertainty in their predictions
381 and assesses the fluctuation in these probabilities across the models to demonstrate their variability.

382 **3. Results**

383 **3.1 CMIP6 data bias correction performance**

384 From both regional and seasonal perspectives, the uncorrected raw CMIP6 data show significant
385 discrepancies with ERA5_Land data during the history period (1980-2014). When compared with
386 ERA5_Land data, the uncorrected raw CMIP6 data reveal an average annual precipitation bias of around
387 ± 1800 mm and an average daily temperature bias of approximately ± 12 °C (Figs. 3b and 3e). These
388 notable inconsistencies highlight that using uncorrected CMIP6 data for hydrological modeling would
389 incur considerable inaccuracies. However, CMIP6 data corrected by the MBCn method deviate from
390 ERA5_Land data by less than ± 120 mm of average annual precipitation and ± 0.2 °C of average daily
391 temperature (Figs. 3c and 3f). The bias correction greatly improves CMIP6 data accuracy in the LMR
392 Basin. The corrected CMIP6 data also match the seasonal cycle of ERA5_Land well for both
393 precipitation and temperature (Fig. 3g). Compared to the raw data, the corrected CMIP6 shows much
394 improved spatial and temporal accuracy, leading to more accurate and reasonable analyses for DFAA.

395 **3.2 Calibration and validation for the hydrological model**

396 The daily observed runoff and daily simulated runoff from the THREW model for the calibration period
397 (2000-2009) and validation period (2010-2020) are illustrated in Fig. 4, demonstrating the model's strong
398 performance. Importantly, since there was no massive reservoir construction in the LMR Basin before
399 and during the calibration period (Zhang et al., 2023), the THREW model without the reservoir module
400 is applied for calibration. Meanwhile, the addition of large-scale reservoirs during the validation period

401 allows validation of the THREW model configuration with the reservoir module. Notably, the THREW
 402 model captures runoff fluctuations between wet and dry seasons with high accuracy, achieving an NSE
 403 of at least 0.8 during both periods. This excellent simulation performance extends across both upstream
 404 and downstream regions, emphasizing the robustness of the model under observed conditions.

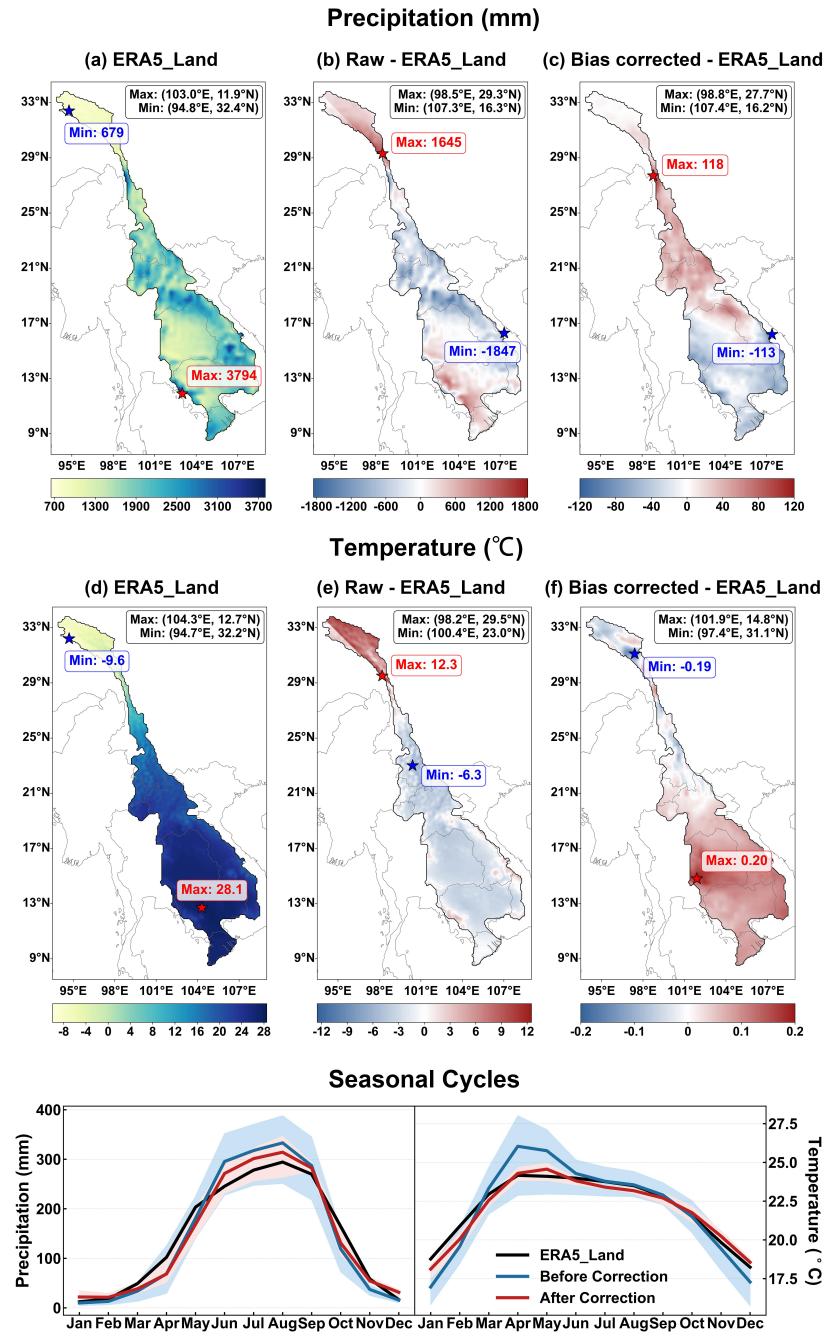
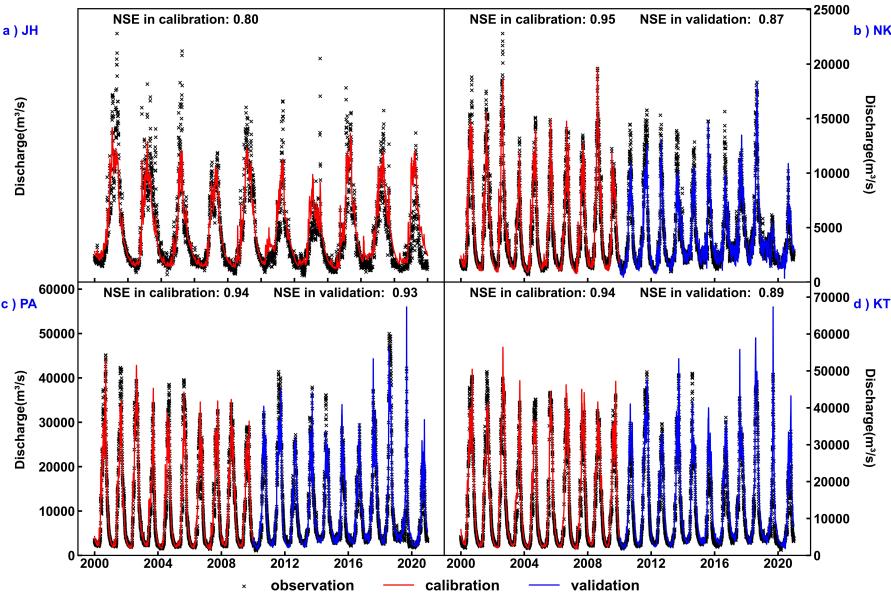


Figure 3: Averaged meteorological data of 5 GCMs for the history period (1980-2014). Here, 5 GCMs are corrected separately. The red and blue star symbols respectively indicate the locations of the maximum and minimum values in (a) to (f). (a) to (c) present the spatial distribution of precipitation based on respectively ERA5_Land, raw CMIP6 (raw CMIP6 minus ERA5_Land) and bias-corrected CMIP6 (bias-corrected CMIP6 minus ERA5_Land). (d) to (f) illustrate the spatial distribution of temperature based on ERA5_Land,

411 raw CMIP6 (raw CMIP6 minus ERA5_Land) and bias-corrected CMIP6 (bias-corrected CMIP6 minus
 412 ERA5_Land). (g) shows seasonal cycles of temperature and precipitation from ERA5_Land, raw and bias-
 413 corrected CMIP6, as well as their corresponding range.



414
 415 **Figure 4: Performance of the THREW model in calibration (2000-2009) and validation (2010-2020) periods.**
 416 Here, JH, NK, PA, and KT denote JingHong, Nong Khai, Pakse, and Kratie stations, respectively.

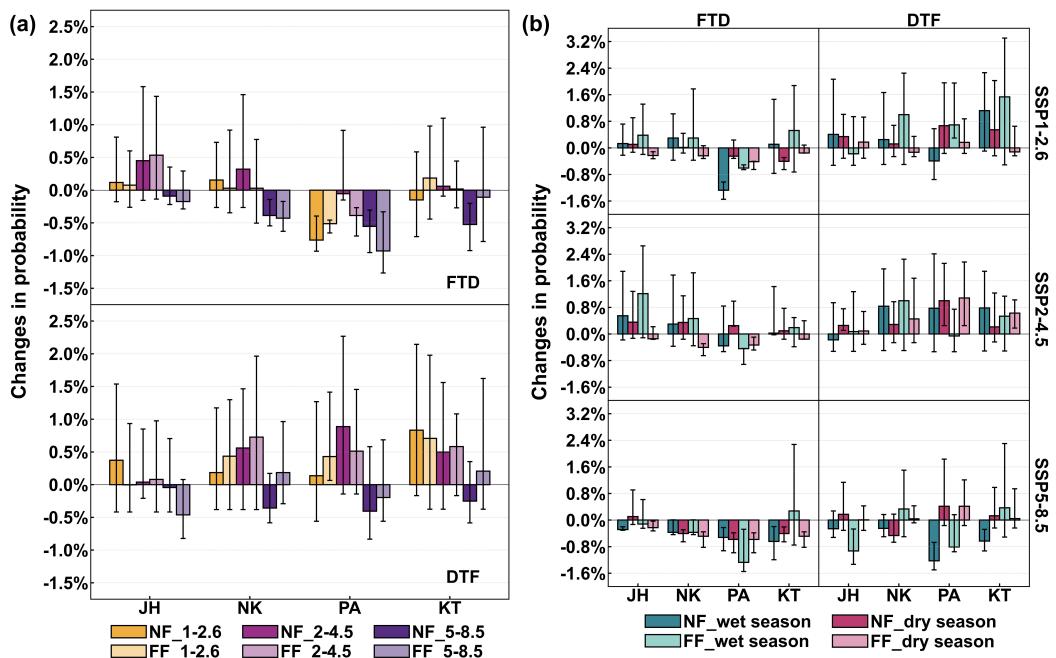
417 3.3 DFAA under the changing climate

418 Under the natural scenario (without reservoir operations), DFAA in the LMR Basin is dominated by DTF,
 419 that is, the risk of DTF is more critical than that of FTD (Table 4). The probability of FTD ranges from
 420 0.7% to 2.1% in the history period, 0.6% to 2.0% in the near future, and 0.5% to 2.0% in the far future.
 421 Conversely, DTF probabilities are higher, ranging from 1.6% to 2.3%, 1.2% to 3.2%, and 1.2% to 3.0%
 422 respectively in these three periods.

423 **Table 4: The year-round DFAA probability averaged across five GCMs during each period under the natural**
 424 **scenario.**

Natural	Station	History	Near Future			Far Future		
			SSP1-2.6	SSP2-4.5	SSP5-8.5	SSP1-2.6	SSP2-4.5	SSP5-8.5
DTF	JingHong	1.67%	2.04%	1.71%	1.63%	1.67%	1.75%	1.21%
	Nong Khai	1.52%	1.71%	2.08%	1.17%	1.96%	2.25%	1.71%
	Pakse	2.24%	2.38%	3.13%	1.83%	2.67%	2.75%	2.04%
FTD	Kratie	2.33%	3.17%	2.83%	2.08%	3.04%	2.92%	2.54%
	JingHong	0.72%	0.83%	1.17%	0.63%	0.79%	1.25%	0.54%
	Nong Khai	1.10%	1.25%	1.42%	0.71%	1.13%	1.12%	0.67%
	Pakse	2.10%	1.33%	2.04%	1.54%	1.58%	1.71%	1.17%
	Kratie	1.86%	1.71%	1.92%	1.33%	2.04%	1.87%	1.75%

425 DFAA risk is substantially elevated during the wet season compared to the dry season (Table S1). For the
 426 average of five GCMs, the probability of FTD in the wet season is 2 to 5.5 times higher than that in the
 427 dry season in the history period. In the near and far future periods, this ratio ranges from 1.1 to 36 times
 428 and 3.3 to 41 times, respectively. As for DTF, the probability in the wet season is correspondingly 1.7 to
 429 5.7 times, 1.3 to 3.9 times, and 0.9 to 6.3 times higher than that in the dry season for history, near future,
 430 and far future. Only JingHong station experiences a slightly higher probability of DTF in the dry season
 431 (1.25%) than in the wet season (1.17%) for the far future.



432
 433 **Figure 5: DFAA under the natural scenario.** (a) The annual change in DFAA probability averaged across five
 434 GCMs and their ranges in the near and far future periods with respect to the history period under three SSPs.
 435 (b) The seasonal change in DFAA probability averaged across five GCMs and their ranges in the near and
 436 far future periods with respect to the history period during wet and dry seasons under three SSPs. Here, JH,
 437 NK, PA, and KT respectively denote JingHong, Nong Khai, Pakse, and Kratie stations. NF and FF represent
 438 the near future period and the far future period. 1-2.6, 2-4.5 and 5-8.5 respectively denote SSP1-2.6, SSP2-4.5,
 439 and SSP 5-8.5 scenarios. Please note that this figure illustrates variations in DFAA events under climate
 440 change. The annual and seasonal probabilities of DFAA under the natural scenario are presented in Table 4
 441 and Table S1, respectively.

442 DFAA risks show marked spatial variation, with annual probability consistently higher downstream than
 443 upstream (Table 4). The annual probability of FTD ranges from 0.6% to 1.3% at JingHong station and
 444 0.7% to 1.4% at Nong Khai station. These probabilities rise to 1.2% to 2.1% and 1.4% to 2.1% at Pakse
 445 and Kratie stations, respectively. Similarly, the annual probability of DTF at JingHong and Nong Khai
 446 stations is 1.2% to 2.1% and 1.2% to 2.3%. The probabilities at Pakse and Kratie stations range from 1.4%

447 to 3.2% and 3.1% to 3.2%, respectively. The DTF risk in the wet season and the FTD risk in both dry
448 and wet seasons are also higher downstream than upstream. Since the probability of FTD in the dry
449 season at Nong Khai, Pakse, and Kratie stations is limited, especially under the SSP5-8.5 scenario
450 (<0.2%), the risk of FTD in the dry season appears more notable upstream than downstream.

451 The annual DFAA probability increases under SSP1-2.6 and SSP2-4.5 scenarios (except for FTD at Pakse
452 station) and decreases under the SSP5-8.5 scenario (Fig. 5a). Such a pattern is attributable to the enhanced
453 tendency for flood and drought events in the LMR Basin to cluster rather than alternate under the SSP5-
454 8.5 scenario (Dong et al., 2022). Under the SSP5-8.5 scenario, the average probability of FTD across
455 five GCMs is 0.6% to 1.8%, while the probability of DTF ranges from 1.2% to 2.6%. Conversely, the
456 average probabilities of FTD and DTF under the SSP2-4.5 scenario range from 0.7% to 2.1% and 1.7%
457 to 3.2%, respectively.

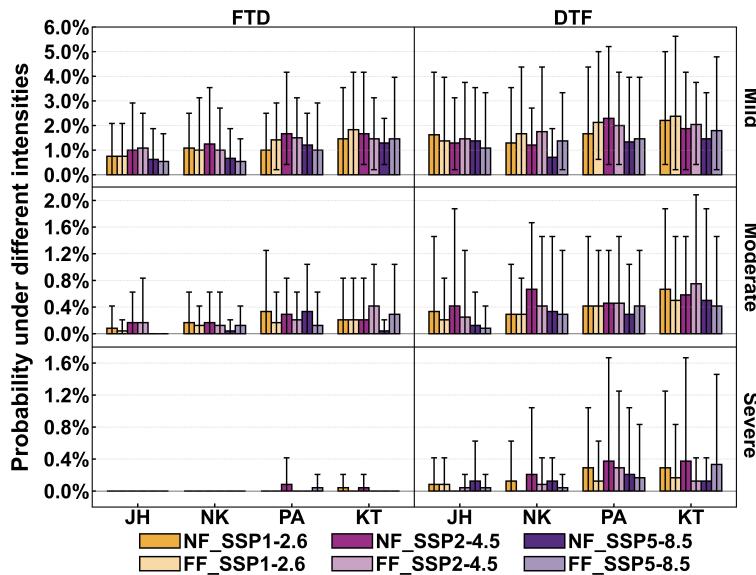
458 The future growth in DTF is significantly greater than that in FTD. For the average probabilities across
459 five GCMs, relative to the history period, the future change in DTF probability at JingHong station is -
460 0.5% to 0.4%, at Nong Khai station is -0.4% to 0.7%, and at Pakse and Kratie stations, respectively, is -
461 0.5% to 0.9% and -0.2% to 0.8%. The future FTD probability change for JingHong is -0.2% to 0.5%,
462 while for Nong Khai, Pakse, and Kratie, the changes are -0.4% to 0.3%, -1% to -0.1%, and -0.6% to
463 0.2%, respectively. The maximum values from the five GCMs show a consistent trend, with increases in
464 DTF probability being significantly greater than those in FTD probability.

465 Upstream and downstream regions experience contrasting future risk increases, with FTD risks rising
466 more upstream and DTF risks rising more downstream (Fig. 5a). Under three climate scenarios, JingHong
467 Station experiences the maximum increase of 0.37% and 0.08% in DTF risks, respectively, in the near
468 and far future. Meanwhile, FTD risks at this station rise by 0.45% and 0.53%, respectively. Conversely,
469 Kratie Station exhibits the highest increase of 0.83% and 0.71% in DTF risks, alongside 0.06% and 0.02%
470 increases in FTD risks. The opposite trends of DFAA risk in upstream and downstream pose enhanced
471 challenges to the integrated management of the LMR Basin.

472 Future seasonal DFAA risks follow scenario-dependent trends: wet-season risks for both DTF and FTD
473 rise under SSP1-2.6 and SSP2-4.5 scenarios, and fall under the SSP5-8.5 scenario (Fig. 5b). This is
474 similar to the annual DFAA risk. The risk of FTD during the dry season decreases, with an upward trend
475 emerging only in the near future under the SSP2-4.5 scenario (average across five GCMs <0.4%,
476 maximum <1.3%). The risk of DTF during the dry season rises in most situations, except at Nong Khai

477 station in the near future under the SSP5-8.5 scenario, where it shows an average decrease of 0.46%
 478 across five GCMs. The largest increase of dry-season risk of DTF is found at Pakse station under the
 479 SSP2-4.5 scenario, with an average increase of 1.08% across five GCMs and a maximum increase of
 480 2.08%.

481 Mild-intensity DFAA events constitute the majority of all DFAA occurrences (Fig. 6). The probability of
 482 mild DTF varies across scenarios, with values ranging from 0.7% to 2.4%, which corresponds to 58% to
 483 90% of the total DTF probability. Likewise, mild FTD probabilities range from 0.6% to 1.8% (Fig. 6),
 484 comprising a larger share of the total FTD probability, specifically 75% to 100%. Mild DTF events
 485 account for 2 to 13 times the possibility of moderate DTF events. This ratio escalates to 3 to 31 times for
 486 FTD events. Notably, severe FTD events are extremely rare, often occurring at 0% probability. However,
 487 severe DTF events are notable, with probabilities ranging from 0% to 0.38%, and in some instances,
 488 accounting for up to 13% of total DTF probability.



489
 490 **Figure 6: Annual probability of DFAA at different intensities under the natural scenario, averaged across five**
 491 **GCMs and their ranges in the near future (2021-2060) and far future (2061-2100) periods under three SSPs.**
 492 **Here, JH, NK, PA, and KT respectively denote JingHong, Nong Khai, Pakse, and Kratie stations. NF and FF**
 493 **represent the near future period and the far future period. The specific value shown in this figure can be**
 494 **found in Table S2.**

495 The total probabilities of DTF events exceed that of FTD events (Fig. 5a), and this holds true for mild,
 496 moderate, and severe intensity events (Fig. 6). The disparity between DTF and FTD events is not as
 497 pronounced in mild intensity events, but it becomes significant in moderate intensity events. The
 498 probabilities of moderate DTF range from 0.08% to 0.75%, whereas the probabilities of moderate FTD

499 range from 0.04% to 0.42% (Fig. 6). The marked disparity in severe intensity events is even more
500 pronounced by the extremely low probability of severe FTD.

501 Mild DTF probabilities are projected to increase in the far future, while moderate and severe DTF
502 probabilities are projected to decrease. Specifically, the probability of mild DTF rises to 1.1% to 2.4% in
503 the far future, compared to 0.7% to 2.3% in the near future. The probabilities of moderate and severe
504 DTF drop from an average of 0.42% and 0.19% in the near future to 0.38% and 0.12%, respectively, in
505 the far future. However, the probabilities of FTD events across all three intensity levels remain relatively
506 consistent between the near and far future.

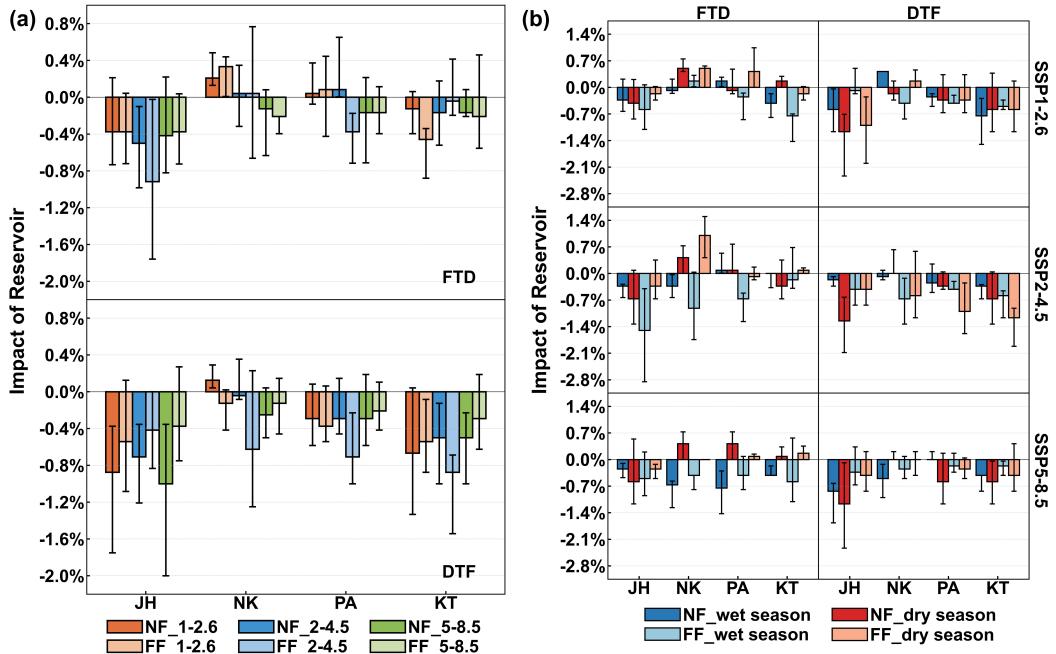
507 **3.4 Reservoirs' impacts on DFAA**

508 Reservoirs exhibit extraordinary mitigation effects on DTF risk under the changing climate while
509 showing weaker effects in FTD risk (Fig. 7a). Nonetheless, the higher probability of DTF compared to
510 FTD (Fig. 5a) demonstrates that reservoirs contribute significantly to reducing overall DFAA risk. The
511 distinct controlling role of reservoirs on DTF risk versus FTD risk is associated with the consistency
512 between these two types of DFAA events and the logic of reservoir operation. Section 4.1 will delve into
513 the mechanistic details.

514 Reservoirs adequately reduce or only slightly increase the future DTF probability (-0.13% to 1%,
515 averaged across five GCMs. Throughout this section, a negative value indicates that reservoirs increase
516 the probability of DFAA, while positive values indicate a reduction. In most scenarios, the reservoir plays
517 a positive mitigating role across all GCMs (Fig. 7a). Reservoirs are expected to have better mitigation
518 effects in the near future at JingHong station. As for Nong Khai and Pakse stations, the reduction effect
519 of reservoirs on DTF is more pronounced in the far future under SSP1-2.6 and SSP2-4.5 scenarios, while
520 in the near future under the SSP5-8.5 scenario. The effect conversely, exhibits greater strength under
521 SSP1-2.6 and SSP5-8.5 scenarios in the near future, while it is stronger under the SSP2-4.5 scenario in
522 the far future at Kratie station. These findings are consistent across both the average of the GCMs and
523 their ranges.

524 Reservoirs are more effective in reducing FTD in the near future than in the far future at JingHong, Pakse,
525 and Kratie, while the effect at Nong Khai is slightly less in the far future (Fig. 7b). Reservoirs are most
526 effective under high emissions (SSP5-8.5), reducing FTD probability at all stations (0.13% to 0.42%,
527 GCM average). Under lower emissions (SSP1-2.6 and SSP2-4.5), mitigation is weaker (-0.33% to 0.38%,

528 GCM average) at Nong Khai and Pakse, but notable at JingHong and Kratie, especially in certain future
 529 periods. For example, under intermediate emissions (SSP2-4.5) in the far future at JingHong, reservoirs
 530 lower the average probability by over 0.9% and maximum by nearly 1.8%.

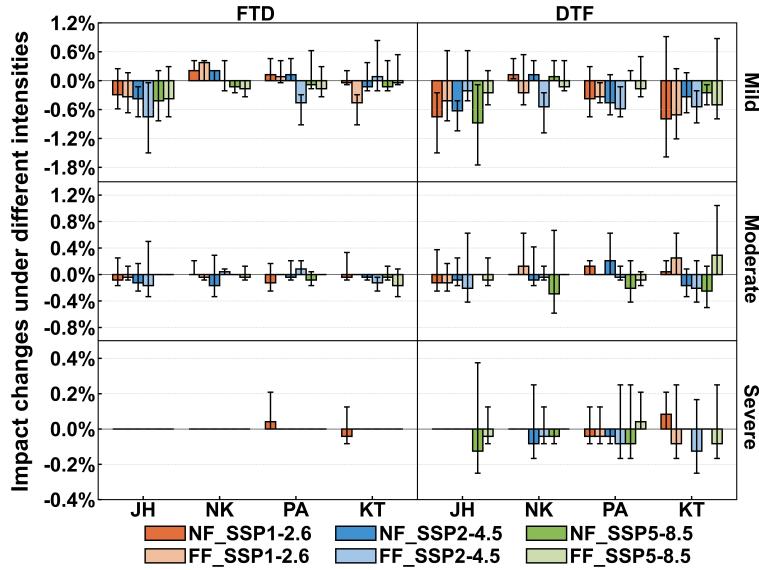


531
 532 **Figure 7: Reservoir impacts on DFAA during the near future (2021-2060) and the far future (2061-2100)**
 533 under three SSPs. (a) The annual reservoir impacts averaged across five GCMs and their ranges. (b) The
 534 seasonal reservoir impacts in wet and dry seasons averaged across five GCMs and their ranges. Here, JH, NK,
 535 PA, and KT respectively denote JingHong, Nong Khai, Pakse, and Kratie stations. NF and FF represent the
 536 near future period and the far future period. 1-2.6, 2-4.5 and 5-8.5 respectively denote SSP1-2.6, SSP2-4.5,
 537 and SSP 5-8.5 scenarios. Please note that this figure illustrates the impact of reservoir operations on DFAA
 538 events. The annual and seasonal probabilities of DFAA under the dammed scenario are presented in Table
 539 S3.

540 Reservoirs reduce FTD more in the wet season (-0.17% to 1.5%, GCM average) than in the dry season
 541 (-1% to 0.67%), especially at Nong Khai, Pakse, and Kratie (Fig. 7b). Negative values mean a reservoir
 542 increases FTD probability. In the wet season, reduction is notable (-0.17% to 0.92%), but in the dry
 543 season, FTD probability increases (-1% to 0.33%). Seasonal differences in DTF mitigation are less
 544 pronounced. Reservoirs slightly better reduce DTF in the dry season (-0.17% to 1.25%) than in the wet
 545 season (-0.42% to 0.83%). Reservoirs mitigate DTF more effectively than FTD in both seasons, aligning
 546 with the annual DFAA.

547 Reservoirs effectively manage DFAA events, which are predominantly characterized by mild intensity.
 548 They decrease the probability of mild DTF by -0.1% to 0.9% (Fig. 8), whereas the probability of such

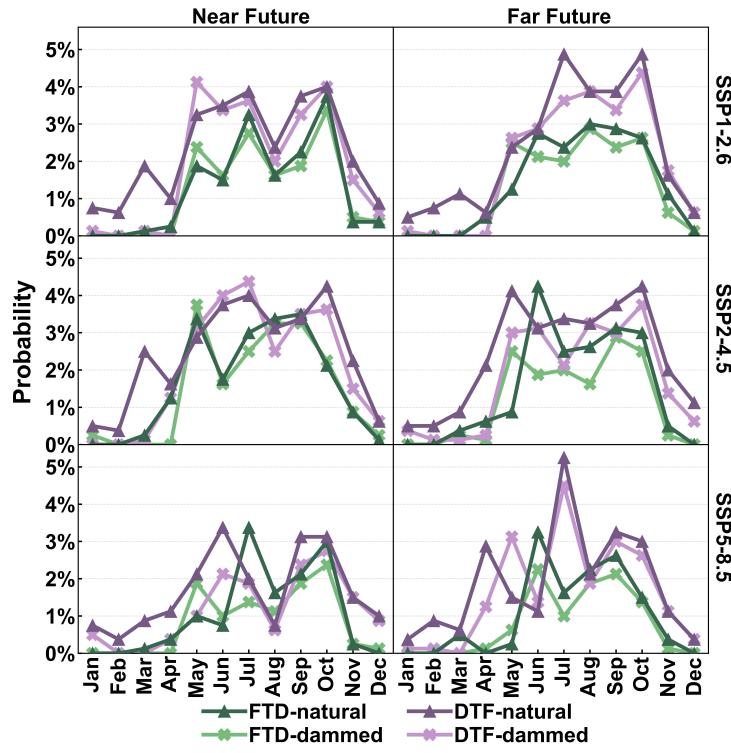
549 events is 0.7% to 2.4% under the natural scenario (Fig. 6), indicating that reservoirs decrease their
 550 likelihood by -0.12 to 0.64 times. Reservoir reduces the probability of mild FTD by -0.4% to 0.8% (Fig.
 551 8). They increase the probability of mild FTD at the Nong Khai station under the SSP1-2.6 scenario.
 552 Since the probability of mild FTD is 0.6% to 1.8% under the natural scenario (Fig. 6), reservoir operation
 553 reduces their probability by -0.38 to 0.69 times.



554
 555 **Figure 8: Reservoir impacts on DFAA under different intensities, averaged across five GCMs and their ranges**
 556 **in the near future (2021-2060) and far future (2061-2100) periods under three SSPs. Here, JH, NK, PA, and**
 557 **KT respectively denote JingHong, Nong Khai, Pakse, and Kratie stations. NF and FF represent the near**
 558 **future period and the far future period. Please note that this figure shows how the reservoir affects DFAA**
 559 **events at different intensities. The probabilities of DFAA events at each intensity under the dammed scenario**
 560 **are presented in Table S4.**

561 While the reservoir's mitigation effect on FTD events is less pronounced than on DTF events (Fig. 7), it
 562 demonstrates a commendable mitigation effect on moderate FTD, reducing their probability by -0.08%
 563 to 0.17% (Fig. 8). This reduction represents -0.4 to 1 times the probability under the natural scenario.
 564 This ratio surpasses the reservoir's mitigation effect on moderate DTF, where the probability is reduced
 565 by -0.3% to 0.3% (Fig. 8), accounting for -0.70 to 1 times the natural probability. This highlights that the
 566 reservoir exerts a more significant mitigating force on high-intensity FTD events compared to high-
 567 frequency FTD events.

568 Reservoirs exhibit notable mitigating effects for DTF events across all three intensity levels. However,
 569 their ability to alleviate moderate DTF is relatively weaker than that for mild DTF (Fig. 8), which differs
 570 from the characteristic of FTD events. This implies that reservoirs possess a stronger capability to manage
 571 high-frequency DTF events than higher-intensity events.



572

573 **Figure 9: Monthly DFAA probability averaged over four mainstream hydrological stations (i.e., JingHong,
574 Nong Khai, Pakse, and Kratie stations) under natural and dammed scenarios for three SSPs during the near
575 future (2021-2060) and far future (2061-2100) periods. Please note that the probabilities shown in this figure
576 are averaged over 5 GCMs.**

577 DFAA often shows several monthly peaks under the natural scenario. This means some months have a
578 higher DFAA probability than their neighbors. The multiple peaks are clearer in DTF than in FTD (Fig.
579 9). When averaging monthly DFAA over four mainstream hydrological stations, DTF shows three peaks
580 under near-term SSP2-4.5 and far-term SSP5-8.5 scenarios, while FTD only shows two peaks in both
581 cases. Reservoirs help to regulate DFAA by lowering and reducing peaks, with a stronger peak reduction
582 effect anticipated in the near future for DTF (Fig. 9). In the far future, for FTD, especially under SSP1-
583 2.6 and SSP2-4.5, reservoirs still alleviate peaks, though less so in terms of reducing their number.
584 Reservoirs also lower DFAA probability during early and middle dry seasons (December to April) for
585 both near and far futures, often 1% or less at most stations. Sometimes, such as the SSP2-4.5 scenario in
586 the near future, reservoirs actually increase the probability of DFAA in May. This happens because
587 helping during the dry season before May reduces the capacity of reservoirs for water regulation in May,
588 making it hard to control DFAA risks that month. Reservoirs also shorten DFAA's monthly span. Instead
589 of occurring throughout the year under the natural scenario, DFAA is concentrated from May to
590 October under the dammed scenario (Fig. 9). This allows the LMR Basin to focus DFAA policies and

591 actions on those months. As a result, riparian states can combine resources and coordinate their efforts
592 more efficiently to manage and respond to DFAA and related hazards.

593 **4. Discussion**

594 **4.1 Different characteristics of DTF and FTD events**

595 The distinct characteristics of DTF and FTD events have been identified by previous research. Shi et al.
596 (2021) found that FTD events predominate in the Wei River Basin. Wang et al. (2023) projected that in
597 the Poyang Lake Basin, the temporal spread of DTF events will expand in the future, while that of FTD
598 events will constrict. Ren et al. (2023) found that under SSP1-2.6 and SSP2-4.5 scenarios, the Huang-
599 Huai-Hai River Basin will experience more DTF events, whereas under SSP3-7.0 and SSP5-8.5 scenarios,
600 it will experience more FTD events. This study identifies differences between DTF and FTD events as
601 well, and further highlights the different characteristics of reservoirs' mitigating effects on these events.
602 The average probability of DTF across all periods is 2.1% under the natural scenario, which is
603 significantly higher than the 1.4% average for FTD (Fig. 5a). The probability of DTF consistently
604 exceeds that of FTD under three different intensities (Fig. 6). Additionally, DTF probabilities show a
605 significant increase in both the near and far future, averaging 0.23%, which exceeds the increase in FTD
606 probabilities, averaging 0.13% (Fig. 5a).

607 Compared with FTD events, reservoirs more effectively control DTF probabilities, significantly lowering
608 DTF risk in both dry and wet seasons (Fig. 7). The reason is that the timing of DTF's water regulation
609 matches the way reservoirs operate. At the start of DTF, reservoirs typically hold water at the storage
610 corresponding to the normal water level, which equates to 0.8 times the maximum storage (Eq. (20)).
611 Hence, reservoirs possess sufficient storage capacity to mitigate the drought conditions. In parallel, the
612 water release during the initial phase of the DTF reduced the water level, thereby meeting the storage
613 needs for sudden floods that occur later in the DTF. As a result, even if DTF events are frequent,
614 reservoirs can manage them well. Reservoirs especially succeed in reducing mild DTF events (Fig. 8).
615 However, they control moderate DTF events less effectively. In intense DTF cases, the rules for operating
616 reservoirs are not enough. For example, if a severe drought at DTF's beginning exceeds reservoir storage,
617 they cannot effectively relieve the extreme drought and thus fail to control such DTF events.
618 Although FTD is less likely than DTF, reservoirs control FTD less effectively, especially in the dry season

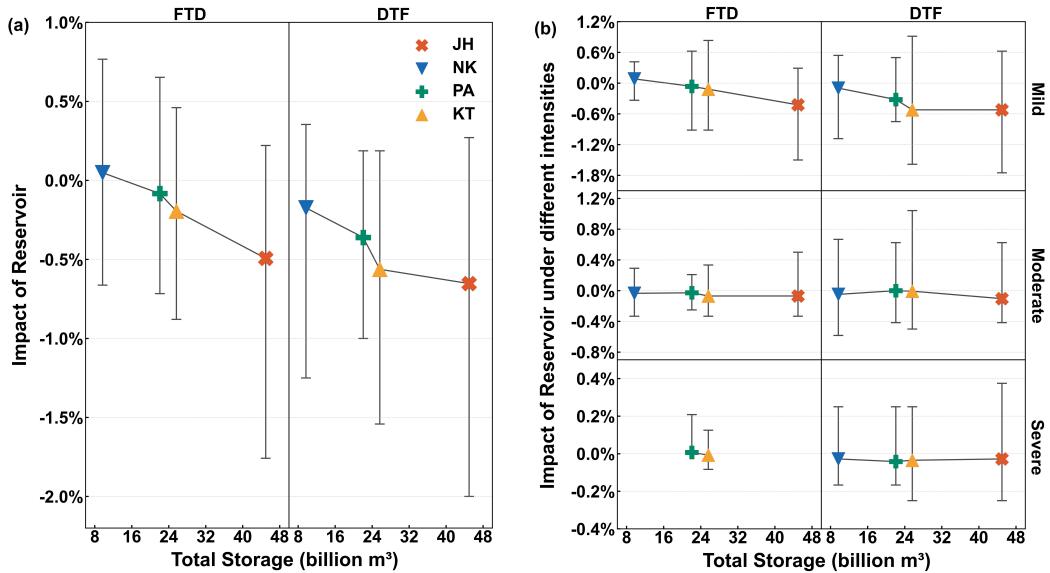
619 (Fig. 7). The problem is that when the FTD event occurs, reservoirs are generally maintained at their
620 target storage for the wet season. The storage corresponds to the flood control water level, which is 1.2
621 times the minimum storage capacity (Eq. (19)). Consequently, reservoirs, while fully meeting flood
622 control requirements at the start of FTD, struggle to maintain sufficient water storage to satisfy water
623 supply demands for the subsequent drought stage. If FTD occur frequently, reservoirs' control decreases
624 further. While reservoirs do little for mild FTD, they noticeably reduce moderate FTD (Fig. 8). This
625 means that, for rare but strong FTD events, reservoirs can help by storing water for later droughts.
626 However, if FTD is frequent, current reservoir operations do not help much. This difficulty in regulation
627 is what makes FTD a major challenge. It is encouraging, though, that FTD is expected to become less
628 common in most areas of the LMR Basin in the future (Fig. 5).

629 **4.2 The relationship between reservoirs' mitigation roles and their storage**

630 The reservoir systems provide enhanced mitigation efficiency against DFAA at JingHong and Kratie
631 compared to those at Nong Khai and Pakse (Fig. 7). Reservoir storage in the region above JingHong and
632 the Pakse to Kratie region is significantly larger than storage in the JingHong to Nong Khai and Nong
633 Khai to Pakse regions (Fig. 1c). Reservoirs' capacity to reduce total DFAA risk closely relates to the total
634 storage of mainstream and tributary reservoirs, consistently showing a positive correlation for DTF and
635 FTD events (Fig. 10a). These findings highlight reservoirs' multifaceted role in managing flood
636 prevention and drought resistance (Hecht et al., 2019; Hoang et al., 2019; Ly et al., 2023) while also
637 addressing sudden DFAA challenges. These results align with Feng et al.'s (2024) discovery that large
638 reservoirs significantly reduce drought and flood risks and corroborate Ehsani et al.'s (2017) conclusion
639 that increased dam dimensions can mitigate water resource vulnerability to climate uncertainties.

640 The positive correlation between total reservoir storage and the reduction of total DFAA risk indicates
641 that basins with larger total storage are better equipped to resist DFAA events. However, this study
642 examines only hydroelectric reservoirs in the LMR Basin and excludes other water storage facilities such
643 as irrigation reservoirs. In the LMR Basin, total storage of irrigation reservoirs is considerable. According
644 to the MRC, the Mekong Basin contains 1317 irrigation reservoirs, with total storage of about 17 billion
645 m³ (MRC, 2018; LMC and MRC, 2023). This storage exceeds the total storage of reservoirs between
646 JingHong and Nong Khai stations (around 9.7 billion m³). It is slightly lower than the storage between
647 Nong Khai and Pakse stations (approximately 22.1 billion m³) (Figs. 1c and 10). Since reservoirs mitigate

648 extreme hydrological events regardless of their primary function (Brunner, 2021a; Ho and Ehret, 2025),
 649 even irrigation reservoirs can play a beneficial role in addressing DFAA events. Fully utilizing irrigation
 650 reservoirs and implementing coordinated operation of all reservoir types across the LMR Basin could
 651 effectively lower DFAA risks and enhance the basin's resistance to these events.



652
 653 **Figure 10: The relationship between reservoirs' mitigation effects and their total storage.** Symbol points
 654 denote the average values for each station under three SSP scenarios during the near future (2021-2060) and
 655 far future (2061-2100) periods, while error bars indicate the maximum and minimum values. (a) The impact
 656 of reservoirs on the total probability of DFAA. (b) The impact of reservoirs on DFAA of different intensities.
 657 Here, JH, NK, PA, and KT respectively denote JingHong, Nong Khai, Pakse, and Kratie stations. Please note
 658 that, as JingHong and Nong Khai stations are not expected to experience severe FTD events in the future, the
 659 relevant information has not been included in this figure.

660 Both mild DTF and mild FTD show a positive correlation with total reservoir storage, consistent with
 661 total DFAA events (Fig. 10b). In contrast, moderate and severe DFAA events do not strongly correlate
 662 with reservoir storage (Fig. 10b). This implies that for moderate to severe DFAA events, increasing
 663 reservoir storage capacity does not enhance the reservoirs' control capabilities. Therefore, refining
 664 reservoir operation rules presents a more appropriate strategy to strengthen control of moderate and
 665 severe DFAA events in the LMR Basin.

666 **4.3 Limitations of reservoir regulation rules**

667 The reservoir operation rule SOP adopted in this study is a commonly used method. Previous studies
 668 have widely employed this method (Wang et al., 2017a; Yun et al., 2020). The SOP rule is proven
 669 appropriate for hydrological modeling in large-scale basins such as the LMR Basin. It is also effective

670 for extended simulation periods in future hydrological assessments (Wang et al., 2017b; Yun et al., 2021a;
671 Yun et al., 2021b).

672 This study further improved the standard SOP operation rules by adding the general case and emergency
673 case (Fig. 2). This scheduling approach manages reservoir operations using real-time inflow data. It also
674 considers the operational year of each reservoir. As a result, the reservoir module developed in this study
675 is robust and adaptable. It reflects reservoir scheduling scenarios with high reliability.

676 Despite this, the study uses uniform operation rules for reservoirs of different storage scales within the
677 LMR Basin. It implements daily regulation for all reservoirs. The study does not use differentiated
678 regulation scales (daily, annual, or multi-annual) based on storage. It also does not consider unique
679 operation rules in different sub-basins. These simplifications may cause uncertainties in how reservoirs
680 mitigate effects. This is a limitation of the study.

681 **5. Conclusion**

682 This study adopts CMIP6 meteorological data, applying three SSP scenarios and five GCMs. It corrects
683 these data using the MBCn method. The study integrates the THREW distributed hydrological model
684 and the developed reservoir module. It describes DFAA through R-SDFAI, assessing mild, moderate, and
685 severe intensities. The study explores how reservoirs help reduce DFAA under the changing climate in
686 the LMR Basin. It examines three periods: history (1980-2014), near future (2021-2060), and far future
687 (2061-2100). The main findings are summarized below:

688 1. DFAA in the LMR Basin is dominated by DTF, with a mean probability of 2.1%. This is much higher
689 than the FTD probability of 1.4%. DTF remains higher than FTD at all intensity levels. The future
690 increase in DTF probability (average 0.23%) is also greater than the increase for FTD (average 0.13%).
691 Mild-intensity DFAA events are most common. They account for 58% to 90% of future DTF probability
692 and 75% to 100% of FTD probability. Both DTF and FTD present higher DFAA risk during the wet
693 season than the dry season.

694 2. Reservoirs manage DTF probability well, cutting DTF risks in both dry and wet seasons. However,
695 they have less influence over FTD risks, especially during dry-season FTD events. Limited capacity to
696 control FTD risks is a challenge. Reservoirs do better at managing high-frequency DTF and high-
697 intensity FTD events. They also cut down multi-peak DFAA events and reduce their monthly duration.

698 3. Reservoirs' ability to lower DFAA total risk is linked to their combined storage. Using large irrigation
699 reservoirs within the LMR Basin can help withstand mild DFAA risks and overall events. To better handle
700 moderate and severe DFAA events, reservoir operations need to be optimized.
701 This study gives new insights into how reservoirs help mitigate DFAA in the LMR Basin. It also aids
702 water management for riparian countries. DFAA remains a serious challenge. This shows the need for
703 LMR Basin countries to work together, build capacity against DFAA events, reduce climate change
704 effects, and support sustainable development.

705 **Author contribution**

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

710 **Competing interests**

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

713 **Data availability**

714 The hydrological data can be accessed and requested from the MRC Data Portal
715 (<https://portal.mrcmekong.org/home>, last access: October 2025). Information related to dams is available
716 on the Mekong Region Futures Institute (MERFI) website (<https://www.merfi.org/mekong-region-dams-database>, last access: October 2025). The raw CMIP6 data without correction is available at (<https://esgf-node.llnl.gov/search/cmip6/>, last access: October 2025). The MBCn algorithm can be accessed and
717 implemented through an R package, which is available at (<https://CRAN.R-project.org/package=MBC>,
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