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Key Points:

- Current methods suffer either from the inability to isolate dam-induced impacts or from the limitations of physical modeling
- We propose a satellite-modeling hybrid framework to evaluate the hydrological impacts of dams in the Lower Mekong River basin
- The most significant changes in inundation dynamics were observed during the decade 2010s when the majority of dams became operational

Supporting Information:

Supporting Information may be found in the online version of this article.

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Assessing Impacts of Hydropower Development on Downstream Inundation Using a Hybrid Modeling Framework Integrating Satellite Data-Driven and Process-Based Models

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Abstract Despite its energy benefits, hydropower dam development often causes ecological damages and social disruption, including downstream livelihood impacts, and biodiversity loss. Current methods for analyzing changes in downstream inundation extent due to dam operation typically rely on historical ground or satellite observations, or on coupled hydrological-hydrodynamic modeling. However, while the former fails to isolate hydropower impacts from climate variations, the latter suffers from extensive input data requirements and high computational burden. This study proposes a novel hybrid framework integrating satellite data-driven Forecasting Inundation Extents using REOF (Rotated Empirical Orthogonal Function) analysis (FIER), and the process-based Hydrological Predictions for the Environment (HYPE) model incorporating the Integrated Reservoir Operation Scheme (IROS). The framework enables the isolated assessment of long-term hydropower impacts on downstream inundation dynamics with computational efficiency and reduced ground data requirements, making it suitable for poorly gauged regions. Applying FIER-HYPE-IROS to the Lower Mekong River basin (LMB), a region significantly affected by dam proliferation impacting fisheries and agriculture, we found that dam operations decreased decadal-average wet season water levels by up to 5% and increased dry season levels by up to 11%. Wet season inundation occurrence decreased by 11 days and the inundated area by 6%, while dry season inundation occurrence extended by 6 days and the surface water area increased by 40%. Although the current framework does not explicitly assess the downstream hydrological modifications, it offers a cost-effective alternative for evaluating upstream alterations on inundation dynamics, such as dam operations, particularly in poorly gauged regions.

1. Introduction

Rising energy demands and campaigns to reduce fossil-fuel dependence have driven the rapid development of hydropower on the mainstems of the world's major rivers (Zarfl et al., 2015). It is estimated that 71% of global renewable energy is accounted for by hydropower (Rex et al., 2014). Since the 1960s–1970s, hydropower dam development in developed countries substantially declined due to environmental and social concerns; however, a rapid proliferation of dam construction and planning has been prominent in the developing regions of the world (e.g., Mekong River Basin, Amazon River basin, and Congo River Basin) (Moran et al., 2018). Dam and reservoir operation offer numerous benefits including renewable energy production, flood control, irrigation, and domestic water supply. However, they have also been found to contribute to the loss of wetlands, dam failures related flood catastrophes, and negative impacts on fisheries production, as well as sediment and nutrition transport (Grill et al., 2019; Nilsson et al., 2005; Tilt et al., 2009; Tran et al., 2023a). These negative effects of dam and reservoir operations can severely impact the aquatic biodiversity and the livelihoods of communities reliant on surface water availability for fisheries and agriculture (Beyene et al., 2012; Chaudhari & Pokhrel, 2022; Soukhaphon et al., 2021). Due to the alarming number of planned hydropower dams in the future, it is imperative

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to be able to assess the effects of hydropower development on a region's hydrological characteristics and inundation dynamics.

Table 1 summarizes several notable studies that have addressed the hydrological impacts of dam constructions on inundation dynamics using different approaches. Two prevalent approaches for assessment of dams and reservoirs' impacts on inundation dynamics include (a) assessing observed hydrological data and/or historical satellite remote sensing, and (b) utilizing physical models (e.g., integrated/coupled hydrological-hydrodynamic or hydrological floodplain models). Observations-based studies (Talukdar & Pal, 2017; Wang et al., 2020) have the advantages from the robustness of not relying on modelling and can reasonably assess the regional hydrological changes pre- and post-dam. However, these changes are the results of both natural (climate change) and human (dams and reservoirs operation) impacts, which cannot be separated using observation data alone. Additionally, this approach is limited by the availability of observed hydrological data and satellite imagery, meaning it can only capture inundation dynamics on days when ground-truth surveys are conducted or when the satellite instruments pass over the study area.

Compared to the first approach, the second approach can effectively isolate the hydrological impact of dams and reservoirs from those of climate change and other anthropogenic factors. This is achieved by comparing two scenarios: (a) a natural baseline with no dams and (b) the current reality with existing dams across the basin. The second approach couples physical models with reservoir operation schemes to simulate the regional hydrological regime and flood inundation under various scenarios (Angarita et al., 2018; Fleischmann et al., 2019; Hatchard et al., 2023; Pokhrel, Burbano, et al., 2018; Shin et al., 2020). However, when using hydrodynamic models, significant computational power is required, and there are several sources of errors and uncertainties in, including (a) digital elevation model (DEM) and channel bathymetry data, (b) friction coefficients to represent energy loss mechanisms, and (c) information about hydraulic structures within the reach (Bates et al., 2014). Despite considerable improvements in the computational efficiency through parallel computing (Neal et al., 2018) and high-performance graphics processing units (GPUs) (Xia et al., 2019), these hydrodynamic models still impose a heavy computational burden (Bhola et al., 2018). Meanwhile, hydrological floodplain models, though less data-intensive and computationally demanding than hydraulic models (Andersson et al., 2017; Hatchard et al., 2023), do not directly reproduce actual inundation extents. Furthermore, this approach faces challenges in ungauged basins, where obtaining reservoir bathymetry data and operation rule curves is difficult.

In this study, we introduce a novel framework that offers an alternative approach to the existing methods for assessing the impacts of dams and reservoirs on inundation dynamics. This framework incorporates the uses of satellite data-driven Forecasting Inundation Extents using Rotated Empirical Orthogonal Function (REOF) analysis (FIER) (Chang et al., 2020, 2023) for daily inundation mapping (details in Section 3.3), along with the process-based hydrological model Hydrological Predictions for the Environment (HYPE) (Lindström et al., 2010), which includes the Integrated Reservoir Operation Scheme (IROS) (Du et al., 2022) (details in Section 3.1 and 3.2). The FIER approach couples the Synthetic Aperture Radar (SAR) satellite images with hydrological data through the REOF analysis (Kaiser, 1958; Lorenz, 1956) to produce accurate and reliable daily inundation maps (Chang et al., 2020, 2023). The hydrological data utilized for FIER is simulated through combined HYPE-IROS modelling under two scenarios: the natural scenario (NAT), representing conditions without dams, and the regulated scenario (DAM), reflecting the operation of existing dams. This framework allowed us to develop two sets of long-term daily inundation maps for the NAT and DAM scenarios. By comparing the difference between these two sets of inundation maps, we can assess the impacts of dams and reservoirs on inundation dynamics.

By directly incorporating satellite-derived inundation maps—which are often used as substitutes for costly ground-truth maps—into the training data set, the proposed framework reduces data accessibility constraints and minimizes the uncertainty errors often associated with hydraulic models in poorly gauged regions. Moreover, FIER is computationally efficient and less data extensive, providing a viable alternative to traditional modeling approaches for scenario analysis. Meanwhile, the HYPE-IROS model has demonstrated its capability in delivering satisfactory hydrological simulations in highly regulated and poorly gauged regions using various satellite data (Du et al., 2020, 2022). Therefore, it is important to explore whether this hybrid approach can effectively analyze the impacts of dams and reservoirs on inundation dynamics.

Although FIER and HYPE-IROS are existing models developed independently for different applications—daily cloud-free inundation mapping for the former and hydrological balance modelling for the latter—the novel aspect

Table 1
Selected Studies in Each Main Approach to Evaluating Impacts of Dams and Reservoirs on Inundation Dynamics

Approaches	Study	Study regions	Objectives	Data & Methods	Pros and Cons
Historical observations (e.g., satellite remote sensing, observed hydrological data)	Talukdar & Pal, 2017	Punarbhaba river basin (5,263 km ²)	Evaluating the impact of rainfall patterns and reservoir induced river flow modification on spatial dynamics of floodplain wetlands.	- Data: Observed rainfall, observed discharges, and Landsat imagery-derived wetland area dynamics - Methods: Using statistical analyses (i.e., simple linear regression, range of variability approach, anomaly estimation) to analyze time series of precipitation, discharges and changes in wetland areas for change detection pre and post-dams.	Pros: - Robust and does not rely on modeling. Cons: - Challenging to separate individual causes. - Challenging to predict a new scenario with planned dams or dam optimization. - Challenging to capture long-term inundation dynamics due to observation frequency and availability of satellite imagery.
	Wang et al., 2020	Tonle Sap Lake (2,500 – 15,000 km ²)	Estimating changes in inundation area and water turbidity in Tonle Sap Lake over the past three decades, identifying the primary factors driving these changes, and determining the linkage between inundation and water turbidity to discuss future implications for the lake.	- Data: Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat-based inundation areas and total suspended sediments (TSS), observed discharges, observed TSS, and other climate variables (i.e., precipitation, evaporation) from global open data sets. - Methods: Conducting statistical analyses (i.e., multiple general linear model) to examine the relationships between precipitation patterns, TSS, and inundation areas from 1988 until 2018.	
Integrated/coupled hydrological-hydrodynamic model	Fleischmann et al., 2019	the Itajai-Açu River Basin (15,000 km ²)	Developing and presenting the application of a coupled large-scale hydrologic-hydrodynamic model incorporating multiple reservoirs to evaluate the relative roles of reservoir and floodplains in mitigating flooding.	- Data: observed daily precipitation, observed long-term climatology data (e.g., wind speed, relative humidity, air temperature, sunlight hours), 1-m high resolution DEM, soil and land use types, and basic reservoir characteristics. - Methods: Coupled MGB hydrologic-hydrodynamic model with reservoir routing.	Pros: - Allowing a more complete representation of hydrodynamic behaviors and extent of flooding events (e.g., river discharge, water depth, flow velocity, and inundation). - Isolating climate- and dam-induced impacts.
	Porkhrel et al., 2018a; Shin et al., 2020; Dang et al., 2022	Mekong's lower floodplain basin	Explicitly evaluating the isolated natural- (climate) and human- (dams and reservoirs) impacts on flood dynamics.	- Data: topography, land cover, soil texture, climate forcing data, gridded irrigated areas, channel width from Global Width Database for Large Rivers, observed discharges, water levels, and basic reservoir characteristics. - Methods: Coupled hydrological HiWG-MAT and hydrodynamics CaMa-Flood, with reservoir operation scheme	Cons: - Inherent drawbacks of hydrodynamic modeling (e.g., computationally demanding, intensive information requirement, uncertainties from boundary conditions and topographic data). - Generic reservoir operation rule due to limited publicly available reservoir rule curves. - Limited consideration to impacts of tidal influences and man-made dykes within the floodplain.

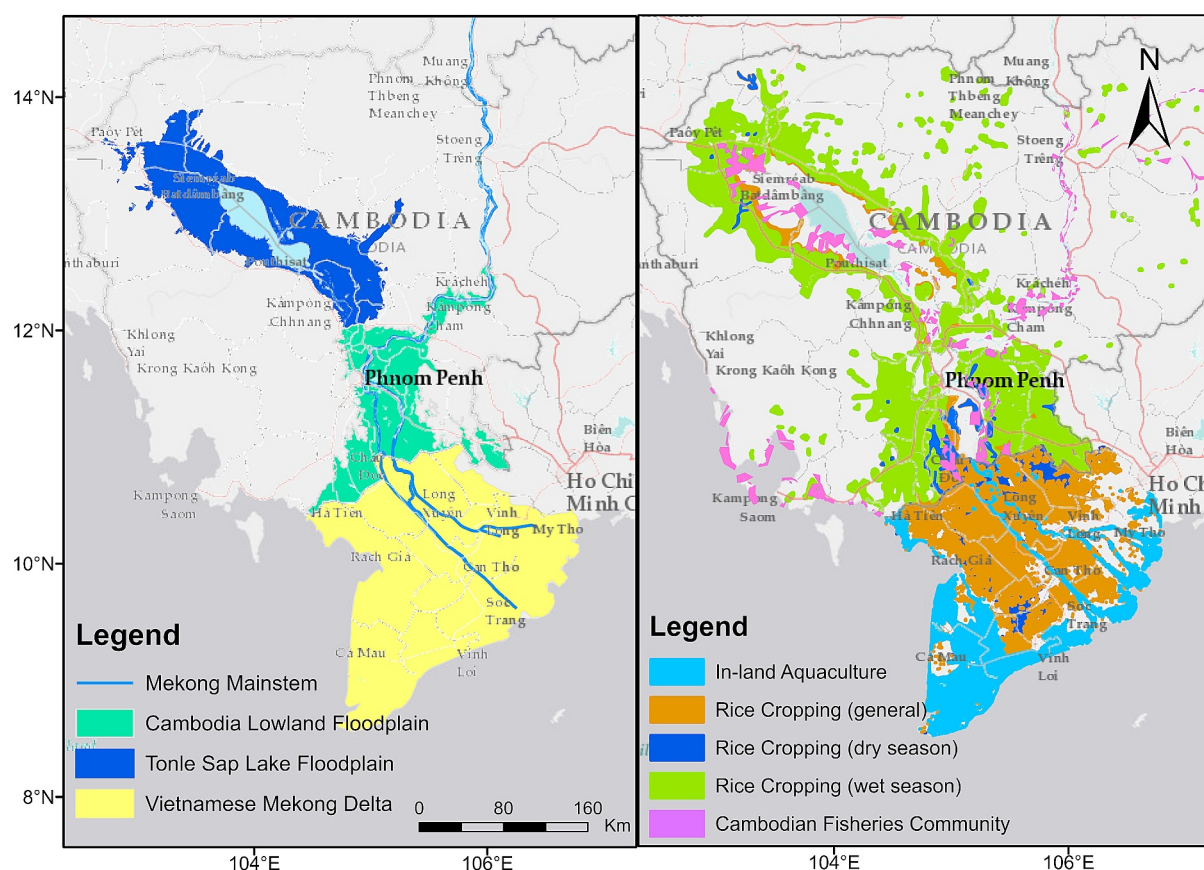


Figure 1. Lower Mekong River basin (LMB) and fishing and agriculture activities (Data source: Vu et al., 2022).

of our framework lies in integrating these models for a new purpose: evaluating impacts of dams and reservoirs on inundation dynamics. To the best of our knowledge, this is the first study to combine a satellite data-based inundation simulation approach with process-based modelling as an alternative method for analyzing dam-induced inundation scenarios. This study serves as a proof of concept, demonstrating how our proposed FIER-HYPE-IROS integrated framework can be utilized to evaluate the anthropogenic impacts of hydropower dams and reservoirs on hydrological balance and inundation dynamics.

Our study area is the Lower Mekong River basin (LMB), a region experiencing rapid hydropower dam development across all basin countries to meet its growing energy demands. The LMB is also highly susceptible to flooding and supports the majority of the region's fisheries and agricultural activities (Figure 1). Considering the heavy dependence of these activities on water availability and their connection to natural flood rhythms, the hydrological impacts of dams and reservoirs are of paramount significance to this region. While many studies have explored the hydrological impacts of dam constructions in the region, both in peer-reviewed literature (Hecht et al., 2019; Keskinen et al., 2012; Räsänen et al., 2017; Sabo et al., 2017) and in local government reports (ICEM, 2010; MRC, 2018; VMNRE, 2015), few have examined the long-term effects of all existing dams across the entire downstream floodplains. Therefore, the understanding of how basin-wide cascading effects of hydropower dams alter inundation dynamics in the LMB remains limited (Shin et al., 2019). To achieve the overall objective of understanding dam impacts on inundation dynamics in the region, this study aims to address the following scientific questions: (a) What are the long-term effects of dams on hydrological balances, assessed through water level analysis, and inundation dynamics, evaluated through water extent mapping? and (b) Is the proposed framework effective in analyzing changes in downstream inundation extents resulting from dam operation?

2. Study Area and Data

2.1. Study Area

The LMB, located downstream of the Mekong River Basin (MRB), is home to the world's largest freshwater fishery and plays a vital role in rice production. Recently, it has undergone a controversial phase of rapid hydropower dam development. Once considered a pristine watershed, MRB has experienced an unprecedented surge in hydropower dams and reservoir construction over the past few decades (Li et al., 2017). Due to its strong topographic gradient and high flow volumes through a network of deep and narrow gorges and steep terrain, the MRB possesses significant hydropower capacity. It is estimated that the MRB's total hydropower potential is around 53,000 MW for the mainstem and 35,000 MW for tributaries (Pokhrel, Burbano, et al., 2018). The existing cascade of dams in the headwaters and along the main stems of the MRB has been scrutinized for their large-scale and transboundary hydrological impacts on Lower Mekong mainstream and floodplains (Stone, 2016). Other studies have also raised concerns about the impacts of dams on streamflow and sediment budgets (Kondolf et al., 2018; Nguyen et al., 2024; Piman et al., 2013) that could potentially lead to adverse and irreversible effects on the basin's natural flow, flood dynamics, and the hydro-ecological functioning of the river (Pokhrel, Burbano, et al., 2018; Sabo et al., 2017; Shin et al., 2019).

These negative effects of dam and reservoir operations can have devastating consequences for the ecology and livelihoods of the MRB and its residents, who heavily rely on fisheries and agriculture. Home to 65 million residents with half of them living near the riverbanks, the MRB's rich and diverse ecosystem has sustained livelihoods and food security for millennia through fishing (Yoshida et al., 2020). The annual fish catch in the MRB is estimated to be 2.0–2.6 million tons/year (Mekong River Commission, 2011) and is valued at US\$ 11 billion/year (Intralawan et al., 2019). Dam-induced changes to the inundation dynamics can disrupt the natural ecology of MRB fishing habitats that rely on the natural flood pulse for spawning and migration (Baran et al., 2003; Sabo et al., 2017). Since fish is the principal source of protein for the region's residents (Orr et al., 2012), the negative impacts of dams on fisheries can lead to inadequate intakes of protein, zinc, niacin, thiamin, riboflavin, and calcium for the majority of the LMB population (Golden et al., 2019). Apart from fisheries, agriculture is another cornerstone of the region that is vulnerable to changes due to hydropower development. Agriculture in the LMB provides the livelihoods for 75% of the residents, accounting for 23.5% of Cambodia's and 31.4% of Vietnam's GDPs (Pokhrel, Burbano, et al., 2018; Yoshida et al., 2020). With the development of hydropower dams, changes in flow volumes and inundation depth in crop fields can negatively impact crop calendars and irrigation/drainage volume (ICEM, 2010). Furthermore, the dam-induced changes in river sediment flows also negatively affect fertilization and crop yields in the region (VMNRE, 2015).

2.2. Sentinel-1 SAR Images

For inundation mapping and FIER analysis, Sentinel-1A VV-polarized Ground Range Detection High-Resolution (GRDH) intensity images from 2017 to 2019 were used. Sentinel-1, comprising two C-band (5.405 GHz) SAR satellite sensors (Sentinel-1A/-1B), is operated by the European Space Agency (ESA) as part of the Copernicus Earth observation program. Only Sentinel-1A imagery was employed to avoid systematic differences in backscattering intensities between the two sensors, and only VV polarization was chosen due to its superior surface water mapping capability (Markert et al., 2020). Four frames (23, 29, 34, and 39) of Path 26 were selected to cover the flood-prone regions of the LMB floodplains and the majority of Tonle Sap Lake periphery, resulting in a total of 85 mosaicked images acquired between 2017 and 2019. The imagery was obtained through the Google Earth Engine (GEE) data catalog, and image pre-processing was carried out using an open-source Python package called Hydrologic Remote Sensing Analysis for Floods (HYDRAFloods). The package can be accessed at (<https://servir-mekong.github.io/hydra-floods/>). Figure 2 presents an illustration of a Sentinel-1A VV backscatter intensity image used for the process. Since the inundation/surface water extent maps in this study were simulated from Sentinel-1 images, the study area and extent mapping are limited to the coverage of the mosaicked SAR images (Figure 2).

Using HYDRAFloods, SAR images obtained from GEE underwent the Gamma Map speckle filtering and slope correction using the Multi-Error-Removed Improved-Terrain Digital Elevation Model (MERIT-DEM) (Yamazaki et al., 2017). Finally, the Global Surface Water Data from the Joint Research Center (JRC) (Pekel et al., 2016) was employed to mask off permanent water bodies and reduce the impact of surface roughness changes on SAR intensities. To enhance the computation speed without significantly affecting the final outcomes, the processed

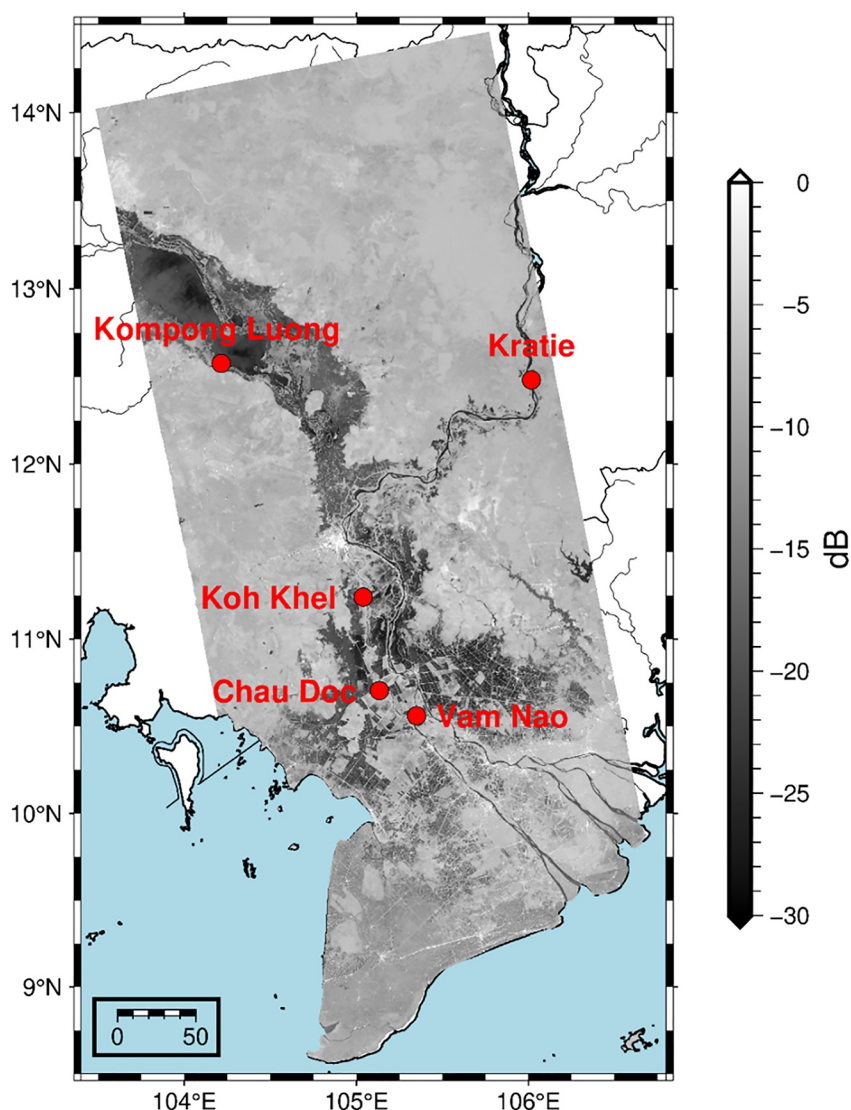


Figure 2. A Sentinel-1A VV-polarized intensity image and locations of relevant water level stations employed in this study.

SAR intensity images and inundation maps were resampled to a spatial resolution of 0.005° (approximately 552 m). It is important to note that while the spatial resolution of this framework is currently set at 0.005° , it can be adjusted to match the input satellite image resolution, which is 10 m for Sentinel-1, especially when requested for operational high-resolution inundation forecasting.

2.3. Hydrological Model's Input Data

In this study, we employed the Greater Mekong-HYPE (GM-HYPE) model, capable of simulating both natural and dam-regulated flows. The GM-HYPE covers a 1.2 million km^2 area, divided into 1,230 subbasins, with an average subbasin area of 1,000 km^2 . Detailed information on the setup of the GM-HYPE model, including meteorological forcing, terrain, land use, natural water bodies, and regulated reservoirs, is available in Du et al. (2020, 2022). The meteorological input for the GM-HYPE model was derived from historical daily data at a spatial resolution of 0.25° . This included merged precipitation from GM-Force (Du et al., 2022) and temperature data from the fifth generation European Center for Medium-Range Weather Forecasts (ECMWF) reanalysis for global climate and weather (ERA5; Hersbach et al., 2020). These data sources informed the model calibration, validation, and meteorological forecast adjustments. Attributes for reservoir data were obtained from multiple

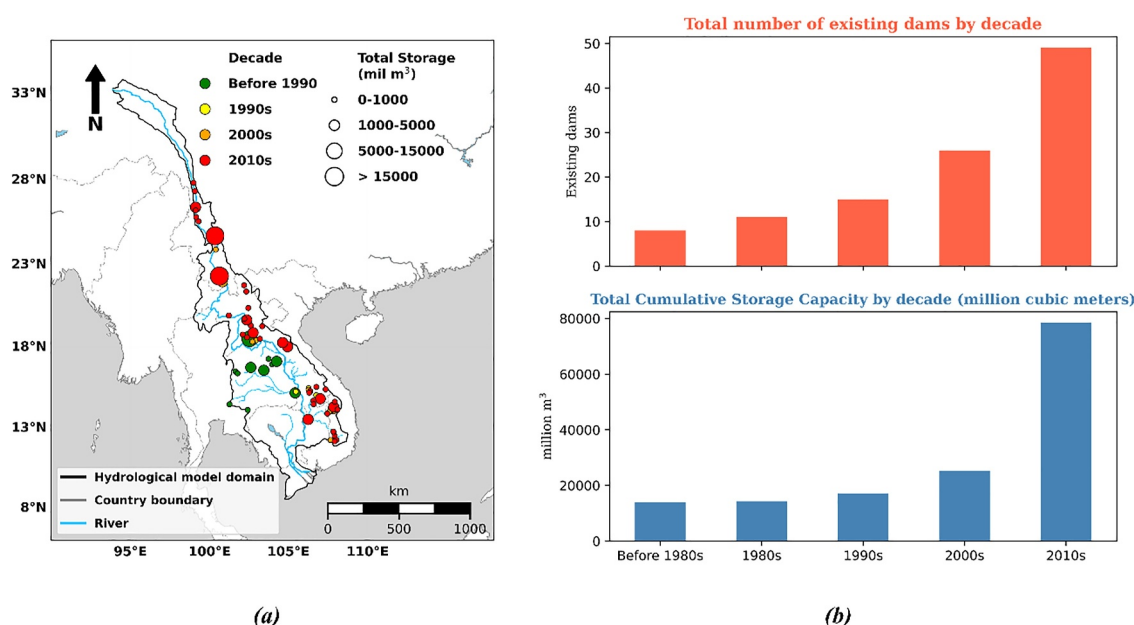


Figure 3. (a) Spatial distribution of MRB operational dams; (b) Temporal distribution of cumulative existing dams and total storage capacity.

sources, including the Global Reservoir and Dam database (GRanD) (Lehner et al., 2011), the Mekong Dam Observatory (WLE Greater Mekong n. d.), and the Vietnam Ministry of Natural Resources and Environment (see Table S1 in Supporting Information S1). Reservoir operation data were validated using observed Vietnamese reservoir data or satellite observations (Du et al., 2022). Additionally, relevant observed water levels in the LMB (locations shown in Figure 2) were provided by the Mekong River Commission (MRC). These observed water level data were used for upstream-downstream water level modeling and for coupling with SAR images to synthesize daily inundation maps.

Figure 3 illustrates the spatiotemporal distribution of 67 existing dams considered in this study. Detailed information about each dam can be found in Table S1 of Supporting Information S1. For ungauged reservoirs, satellite imagery can be used to generate reservoir Area-Elevation-Volumes curves and operation rule curves, as described in Du et al. (2022). Dams included in this study must have accurate geographic locations and information related to total storage capacity. Therefore, dams with inaccurate locations or missing capacity data were excluded. The total storage capacity of the hydropower reservoirs included in this study is nearly 87 billion m³. During the 2010s, an unprecedented surge in dam construction and operationalization occurred in the MRB, nearly doubling the count of existing dams (a 60% increase). This resulted in a remarkable 180% increase in total storage capacity accumulation (see Figure 3b). As a result of these substantial increases in the number of dams and the storage capacity in the 2010s, substantial changes to the region's hydrology due to dams and reservoirs are expected during the period.

3. Method

The FIER-HYPE-IROS framework aims to produce inundation maps for two scenarios: a natural scenario (NAT) where no dams were built, and a regulated scenario (DAM) where existing and operational dams are considered. To achieve this, we used the HYPE hydrological model, which incorporates the IROS (HYPE-IROS), to simulate the water level/streamflow time series for the two scenarios. Since the input data for HYPE-IROS, such as climate forcing, land cover, and water withdrawal, were kept identical across both scenarios, with only difference being the reservoir-related information, any observed differences between them can be attributed solely to the variations in reservoir data. Subsequently, we used the FIER method to couple the simulated time series from HYPE-IROS with SAR images, producing daily inundation maps (i.e., daily binary map of water and non-water pixels) for both scenarios. The daily binary water maps were subsequently used to calculate inundation occurrence (or sometimes referred as surface water occurrence) and inundated area for each decade. The impacts of dams and reservoirs

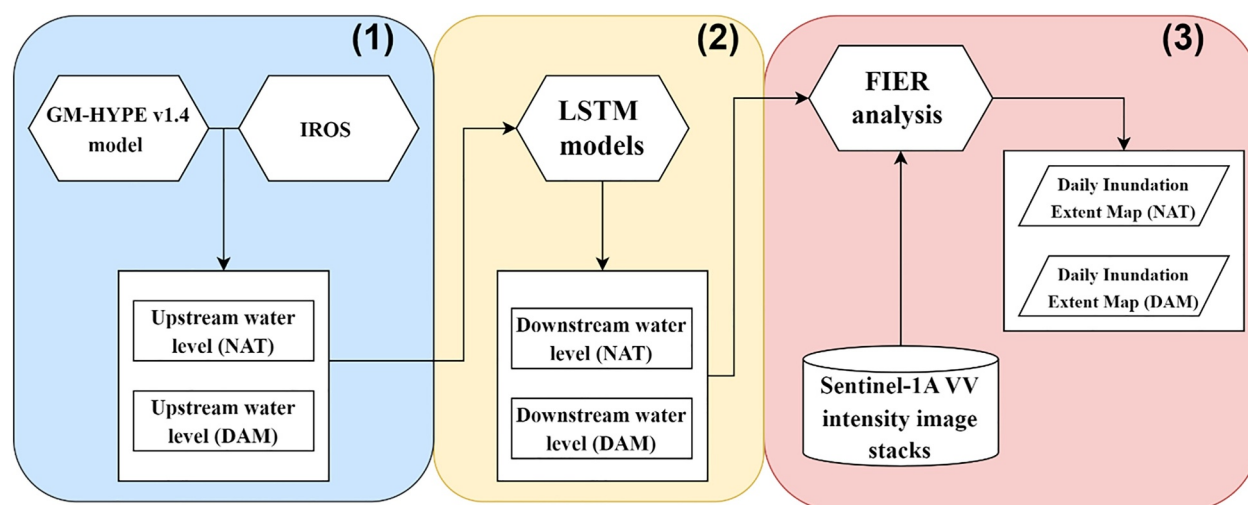


Figure 4. FIER-HYPE-IROS Framework. In this study, upstream water level refers to the water level at Kratie station. Downstream water level refers to the water levels at Kompong Luong, Koh Khel, Chau Doc, and Vam Nao stations. The extended framework for FIER analysis (domain (3)) can be found at Figure S1 in Supporting Information S1.

were quantified by comparing the results from the DAM and NAT scenarios. The decadal inundation occurrence map was calculated on a pixel-wise basis, representing the percentage of days each pixel was classified as water over the total number of days in each decade. The inundated area was calculated by multiplying the number of water pixels by the spatial resolution of the water extent map, which is approximately 552 m. Figure 4 summarizes the framework, which can be divided into three parts: (a) the HYPE-IROS model for deriving water levels upstream of LMB for both scenarios, (b) Long-short-term-memory (LSTM) models to derive downstream water levels from upstream water levels, and (c) FIER analysis process to produce daily inundation maps.

3.1. The Hydrological Predictions for the Environment—Integrated Reservoir Operation Scheme (HYPE-IROS)

3.1.1. Greater Mekong—Hydrological Predictions for the Environment (GM-HYPE) Model

The HYPE model, developed by the Swedish Meteorological and Hydrological Institute (SMHI) in 2005, is a semi-distributed rainfall-runoff and nutrient transfer model. The code is written in FORTRAN for both Windows and Linux systems and is distributed as open source. More details about the model can be found in Lindström et al. (2010) and at hype.sourceforge.net.

The Greater Mekong-HYPE (GM-HYPE) model version 1.4 has undergone incremental development since 2015 and has demonstrated its reliability in modeling streamflow and reservoir outflows across the region in both natural and dam-regulated regions (Du et al., 2020, 2022). The original version, v1.1, was the result of a long-standing collaboration between SMHI and the Vietnamese National Center for Water Resources Planning and Investigation (NAWAPI). The current version, v1.4, has been refined through long-term co-production efforts involving multiple partners, including the University of Houston and NAWAPI. The model was calibrated using both automatic approaches, following the differential evolution Markov Chain (DE-MC) proposed in Ter Braak (2006), and manual stepwise parameters to evaluate physically meaningful parameters. In the latest version, the model was also refined using IROS coupled with satellite-based reservoir operation to model reservoir outflows and regulated streamflow. The calibration and validation of the GM-HYPE model spanned the period from 1991 to 2009, encompassing 58 stations in all river basins in the region (Du et al., 2020). Its additional validation process extended to the post-dam 2016–2019 period, including 29 reservoirs and 9 hydrological stations downstream of cascade reservoirs (Du et al., 2022). Employing various calibration and validation approaches, GM-HYPE achieved a median Kling-Gupta Efficiency (KGE) of 0.72 and a Pearson's correlation coefficient of 0.86 for the pre-dam period (1991–2001), and 0.64 and 0.78, respectively, for the post-dam period (2016–2019).

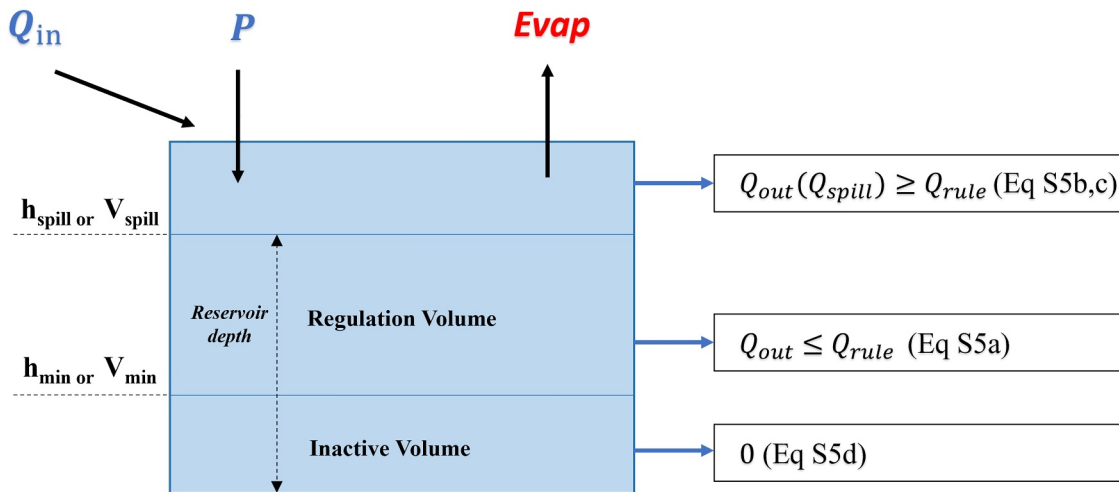


Figure 5. Schematic diagram of Integrated Reservoir Operation Scheme (IROS) (adapted from Du et al. (2022)). Q_{in} , P , and $Evap$ represent reservoir inflow, precipitation, and evaporation, respectively. Q_{out} is the reservoir outflow, calculated from Equations S4–S6. Q_{rule} is the simulated seasonal product flow. Q_{spill} is the reservoir outflow released through the spillway. The minimum water level and volume of the reservoir are denoted as h_{min} and V_{min} , whereas h_{spill} and V_{spill} represent the water level and volume at the spillway. IROS equations can be found in Text S1 of Supporting Information S1.

3.1.2. Integrated Reservoir Operation Scheme (IROS)

Various approaches have been explored for predicting reservoir releases, or regulated streamflow. Some studies have applied calibration functions directly within models, using observed regulated flows (Lauri et al., 2012; Masaki et al., 2017), or incorporating published rule curves (Dang et al., 2020; Zhao et al., 2016). However, such approaches require extensive gauging networks or published rule curves, making them unsuitable for transboundary and poorly gauged basins like the MRB. Alternative studies use a remote sensing–mass balance hybrid approach that combines reservoir inflow data from hydrological modeling with reservoir storage changes derived from satellite imagery and altimetry (Bonnema et al., 2016; Han et al., 2020). Nevertheless, this approach is limited by the temporal resolution of the remote sensing observations. Due to the longer revisit cycle of satellite instruments, the daily reservoir storage time series must be estimated via interpolation or averaging of multi-year satellite operation data. This often results in diminished skill, particularly in the context of cascade reservoir systems (Han et al., 2020).

To address this challenge, the Integrated Reservoir Operation Scheme (IROS) combines the strengths of the hybrid mass balance (MB) method and zoned water levels (i.e., minimum water levels, spillway water levels) simulation (Arheimer et al., 2017; Du et al., 2022) to predict regulated streamflow at poorly gauged regions. Du et al. (2022) found that IROS can satisfactorily model regulated streamflow at both single and cascade reservoir system. Figure 5 shows the schematic diagram of IROS reservoir regulation. IROS is capable of modeling reservoir outflows (Q_{out}), elevations (E), and storage volumes (V) at the same timestep as the forcing data (e.g., hourly or daily). In this study, since we use daily forcing data, IROS outputs are generated at a daily timestep. Q_{in} and $Evap$ represent the reservoir inflow and evapotranspiration, respectively. GM-HYPE v1.4 uses the Penman-Monteith algorithm to estimate evapotranspiration (Du et al., 2020; Mu et al., 2011). Rivers and water bodies are assumed to evaporate at the potential rate when the air temperature exceeds a certain threshold, with evaporation limited by the water body's volume. The parameters for the evaporation process within GM-HYPE v1.4 are detailed in Du et al. (2020). Additionally, it should be noted that although IROS assumes that the reservoir surface area remains constant with depth (Figure 5), it does not model a specific reservoir shape. Instead, it conceptualizes the reservoir as a bucket of water, where inputs such as precipitation and inflow are balanced by outputs like evaporation, outflow, or water withdrawals. While IROS-based simulated reservoir storage volumes are comparable with observed values, this assumption prevents direct simulation of reservoir elevations (h). Consequently, final simulated reservoir elevations (E) are derived through linear interpolation of known elevation–volume pairs, using the Area-Elevation-Volume (AEV) curves derived from Shuttle Radar Topography

Mission Digital Elevation Model (Du et al., 2022; Farr et al., 2007). A detailed explanation of IROS and its governing equations can be found in Text S1 of Supporting Information S1.

The equations for IROS can be found in Text S1 of Supporting Information S1.

3.2. Simulating Water Levels Using HYPE- IROS and LSTM

The HYPE-IROS was used to simulate water levels at Kratie station, influenced by rainfall-runoff and the operation of upstream man-made hydropower dams. Two scenarios, namely NAT and DAM, were considered, covering the period from 1982 to 2021. In the DAM scenario, dams were added sequentially based on their commissioning years, while the NAT scenario was modeled without any dams. The water levels at Kompong Luong (KPL), located in the Tonle Sap Lake (TSL), experience the impact of reverse flows due to river-lake interactions. Meanwhile, other downstream stations experience backwater effect and tidal intrusion from the East Sea (i.e., South China Sea) and the Gulf of Thailand. To effectively capture the inherent nonlinear relationship between the input and output, particularly for reverse flow phenomena, machine learning-based models like Long Short-term Memory (LSTM) have been employed (Morovati et al., 2021; Yao et al., 2023). Consequently, we constructed LSTM models for each station. For KPL, we used the observed Kratie water levels as input data. For the remaining water levels at the three downstream stations (i.e., Koh Khel, Chau Doc, and Vam Nao), which exhibit high correlations with those at KPL and Kratie, we set up multivariate LSTM models. These models incorporated the observed Kratie and KPL water levels (h_{Kratie} and h_{KPL}) as inputs.

LSTM has gained considerable popularity in hydrology, as evidenced by studies such as Sit et al. (2020), Ardabili et al. (2019), and Luo et al. (2020). LSTM is a specialized Recurrent Neural Network (RNN) that is used for long-range sequence modeling. When compared to traditional neural networks, RNNs use their feedback connections to store representations of recent input events in the form of activations, which act as short-term memory, as opposed to long-term memory embodied by slowly changing weights (Rumelhart et al., 1985). This ability enables them to connect previous information to the present task, making them effective in sequential applications such as speech recognition, language modeling, and image captioning. However, traditional RNNs suffer from long-term dependency problems since the temporal evolution of backpropagated errors exponentially depends on the size of the weights and therefore tends to expand or vanish (vanishing gradient problem). In simpler words, RNNs fail to learn in the presence of time lags greater than 5–10 discrete time steps between relevant input events and target signals (Gers et al., 2000). LSTM, on the other hand, enforces constant error flow through constant error carousels (cells) within special units to solve longer time-lag tasks than traditional RNN (Hochreiter & Schmidhuber, 1997). Given the inherent time lag between upstream and downstream water level stations (Chang et al., 2019), simple linear regression proves challenging. Additionally, river flows in the LMB are complicated by backwater flow into TSL during monsoon season. Consequently, methods considering data sequences and can model complex relationships, like LSTM, are better suited to these scenarios and can outperform linear regression.

For each downstream station, we utilized an LSTM model that takes either one input feature (h_{Kratie}) or two input features (h_{Kratie} and h_{KPL}), with a single hidden layer consisting of 16 units. The models were trained using mean squared errors as the loss function and the Adam optimizer with observed data from 1996 to 2021. The observed data was split into 70% for training and 30% for testing to prevent overfitting. Subsequently, the trained models were applied to simulated upstream water levels from the HYPE-IROS, deriving simulated downstream water levels for the entire duration from 1982 to 2020. The simulated upstream water levels from hydrological modeling (Kratie) and LSTM (Kompong Luong, Koh Khel, Chau Doc, and Vam Nao) were then used as input for FIER to generate long-term daily inundation mapping.

3.3. FIER Process and Inundation Extent Mapping

Despite the growing use of SAR imagery in various applications, its deployment for daily operational inundation mapping is hindered by longer revisit times of instruments. To address this, Chang et al. (2020) introduced FIER, establishing an efficient remote sensing-based inundation forecasting system for the LMB with fast runtimes (Chang et al., 2020, 2023). The FIER method performs a Rotated Empirical Orthogonal Function (REOF) analysis (Kaiser, 1958) on a stack of historical Sentinel-1 SAR images to derive spatial variability maps (Rotated Spatial Modes, or RSM) and their corresponding temporal variability time series (Rotated Temporal Principal Components, or RTPC). Interpreting the patterns of RSMs modes (appearance of water bodies like lakes and

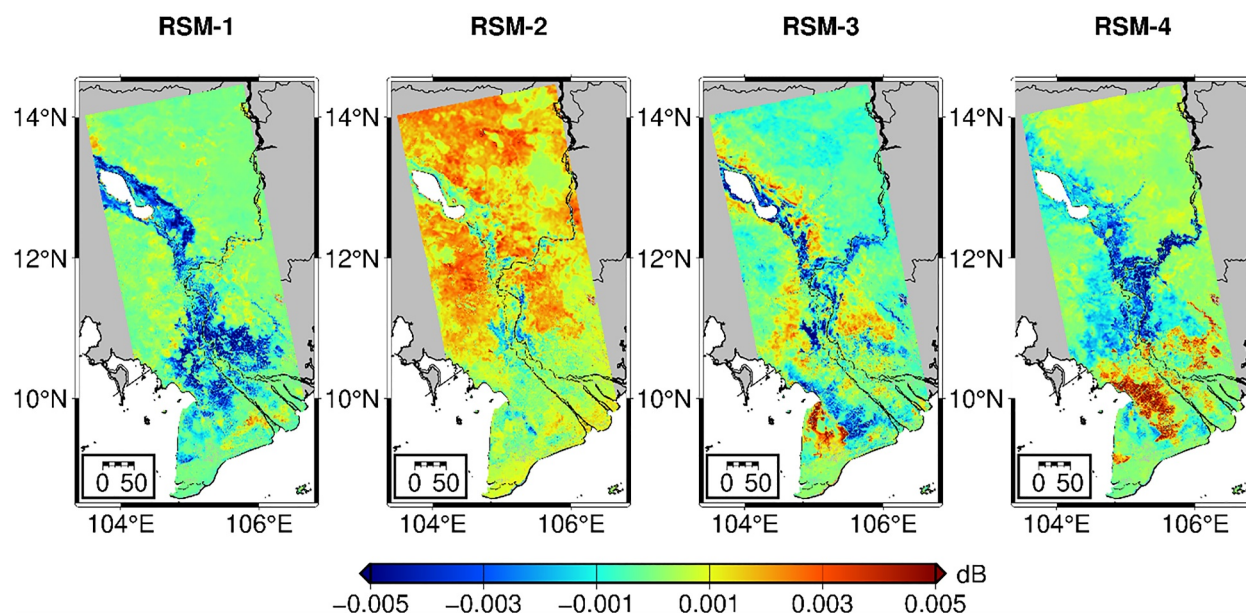


Figure 6. Rotated spatial modes (RSM) of REOF for FIER in the LMB.

rivers) and the RTPCs time series (annual seasonality or peaks representing significant flood events) can help identify water-related modes. The RTPCs are then coupled with historical altimetry-derived or in situ water levels or flow discharge data to build regression models. Future and historic RTPCs are estimated from forecasted and hindcasted streamflow or water levels, integrated with their corresponding RSMs to generate SAR-like images. Finally, forecasted inundation extents are produced using a water classification technique. The REOF analysis and the regression modeling need only to be performed once, unless recent extreme inundation maps require an update, making the FIER method computationally efficient, suitable for large-scale inundation forecasting operations.

The FIER framework has been successfully implemented over the Lower Mekong Basin using an altimetry-based river level forecasting system (Chang et al., 2019, 2020). Recently, a web application for FIER's inundation mapping forecast in the LMB has been developed and can be accessed via <https://fier-mekong.streamlit.app/> (Chang et al., 2023).

For the FIER process, an REOF analysis was performed on 85 Sentinel 1A-VV images from 2017 to 2019 to obtain the significant spatiotemporal patterns. Following Chang et al. (2023), the four most significant modes (highest variance) were selected. As shown in Figure 6, negative pixels (blue) in the RSMs representing water due to the specular backscattering recorded in the SAR images, illustrate different areas of variance (non-water to water) in the image stack. The RTPC of each mode was coupled with the in situ water level station with the highest correlation. Higher water level values result in greater derived RTPC values, leading to lower synthesized SAR intensity results when multiplied with the negative-value pixels in the RSMs. The resulting synthesized SAR intensity negative-value pixels are then classified as water.

To derive daily RTPC values from the LMB downstream water level stations, we built neural network regression (NNR) models between each pair of RTPC and water level data. Since the NNR model does not assume a function for model fit, using this method is more automatic compared to a manual inspection for function order as in Chang et al. (2020). To offset the scale discrepancy between RTPC and water levels, both required normalization before training. The number of hidden layers and units in each layer were obtained through an automatic trial-and-error grid search. We chose the Rectified Linear Unit (ReLU) as the activation function, Adam gradient descent algorithm as the optimizer, and mean squared error as the loss function. Training and validation employed the K-fold cross-validation to prevent overfitting with a minimum fold that represented a full hydrological cycle. Figure 7 depicts the NNR models for four RTPCs and their performance metrics. Using LSTM, we produced downstream water levels (at Vam Nao, Koh Khel, Chau Doc; see Figure 3 for station locations) for scenarios of NAT and DAM. The water levels serve as input for the NNR model to produce daily RTPC values that were

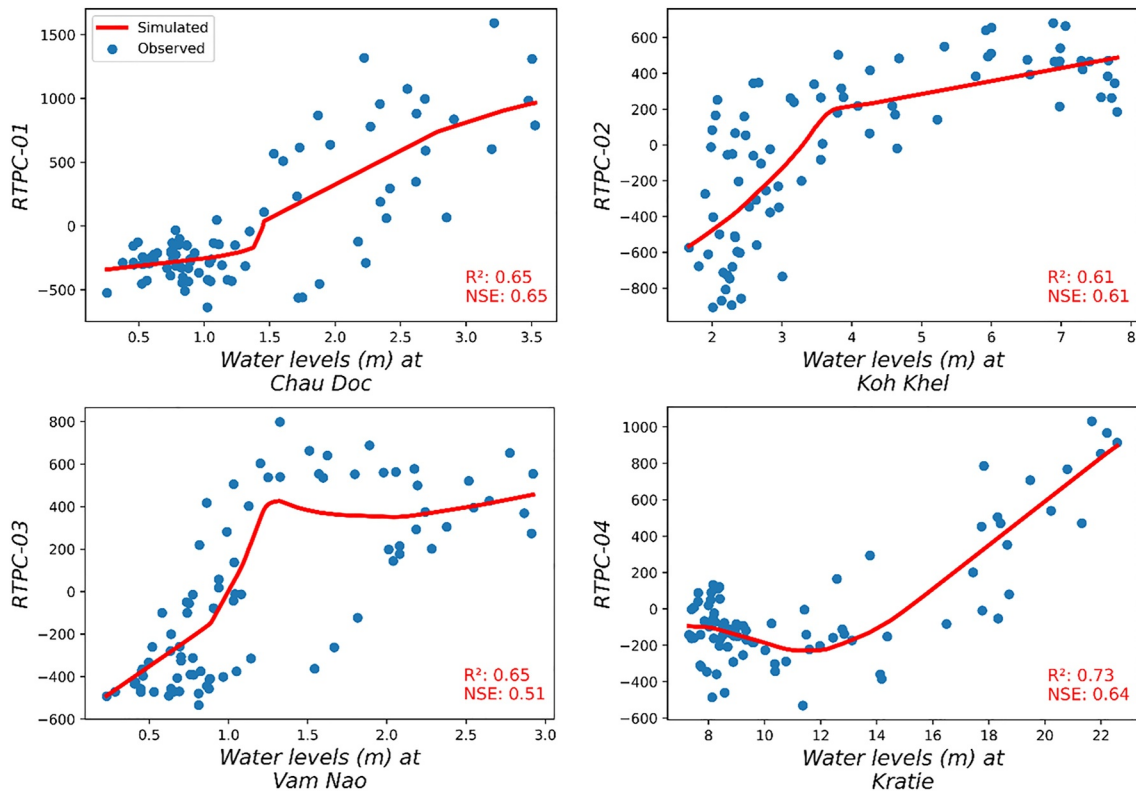


Figure 7. Neural network model and fitting for rotated temporal modes and water level stations.

combined with RSMs to produce the two sets of synthesized Sentinel-1-like images for both scenarios. Finally, inundation maps were generated by performing water classifications on these synthesized SAR-like images.

Many water pixel classification techniques were developed in the past, such as K-means clustering (Arthur & Vassilvitskii, 2006) and the Edge Otsu method (Donchyts et al., 2016). The Z-score method proposed by DeVries et al. (2020) is chosen for its pixel-based calculation process that can be easily parallelized, ensuring high computational efficiency. The Z-score measures the deviation of a pixel value from standard deviation and its proximity to the mean of the group. In this application, the mean and the standard deviation are derived from the SAR images of classified dry days. A high Z-score magnitude indicates a transition from scattering mechanisms of rough land surfaces (e.g., rough soils or vegetation canopies) to specular reflection typical of smooth open water surfaces. Pixels with high-magnitude negative Z-scores exceeding a certain threshold are classified as inundated (water) pixels. Below are the equations for the conventional Z-score and Z-score of SAR image pixels used in DeVries et al. (2020):

$$Z = \frac{x - \bar{x}}{\text{std}(x)} \quad \text{and} \quad (1)$$

$$Z_{\sigma_0} = \frac{\sigma_0 - \overline{\sigma_0^{\text{Dry}}}}{\text{std}(\sigma_0^{\text{Dry}})} \quad (2)$$

where Z is the Z-score that reflects the degree that data x deviate from the mean $\bar{x}$, Z_{σ_0} is the equivalent Z-score of σ_0 SAR intensity image, $\overline{\sigma_0^{\text{Dry}}}$ and $\text{std}(\sigma_0^{\text{Dry}})$ represent the mean, and standard deviation of dry-time SAR intensity images. Based on previous studies (Chang et al., 2023; DeVries et al., 2020), a threshold value of -3 was chosen to obtain the two sets of inundation extent maps for the two scenarios of NAT and DAM.

3.4. Framework Validation

3.4.1. Evaluation of HYPE-IROS and LSTM Simulation

The performance of the simulated water levels was evaluated using the Root Mean Squared Error (RMSE), Nash–Sutcliffe model efficiency (NSE), Correlation Coefficient (R^2), and Kling–Gupta efficiency scores (KGE) (Gupta et al., 2009) that have been used in many studies (Moriassi et al., 2007; Tran et al., 2023b). These metrics are described as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^N (h_i^{\text{sim}} - h_i^{\text{obs}})^2}{N}}, \quad (3)$$

$$\text{NSE} = 1 - \left[\frac{\sum_{i=1}^N (h_i^{\text{obs}} - h_i^{\text{sim}})^2}{\sum_{i=1}^N (h_i^{\text{obs}} - h_{\text{mean}}^{\text{obs}})^2} \right], \quad (4)$$

$$R^2 = \left[\frac{\sum_{i=1}^N (h_i^{\text{obs}} - h_{\text{mean}}^{\text{obs}})(h_i^{\text{sim}} - h_{\text{mean}}^{\text{sim}})}{\sqrt{\sum_{i=1}^N (h_i^{\text{obs}} - h_{\text{mean}}^{\text{obs}})^2} \sqrt{\sum_{i=1}^N (h_i^{\text{sim}} - h_{\text{mean}}^{\text{sim}})^2}} \right]^2, \text{ and} \quad (5)$$

$$\text{KGE} = 1 - \left[\sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \right] \quad (6)$$

where h_i^{obs} and h_i^{sim} denote the observed and simulated water levels and r , α , and β for KGE represent the Pearson linear correlation coefficient, variability bias, and volume bias between the simulated and observed values. While R^2 focuses on proportion of variance explained and RMSE on the average magnitude of errors, NSE evaluates how well the model predicts relative to the mean of observed data, particularly for high flow/level in hydrology (Pushpalatha et al., 2012). Lastly, the KGE metric can indicate the year-round overall performance of the model.

3.4.2. Inundation Map Skill Evaluation

Since there is no observed inundation extent mapping, validating the FIER inundation extent map with in situ data is not feasible. However, the inundation extent mapping from the FIER method in the LMB was cross-compared with the MODIS-derived as well as Sentinel-1-derived inundation maps in the region, achieving a satisfactory Critical Success Index rate in our previous studies (Chang et al., 2020, 2023). In this study, for further framework evaluation, the inundation maps from the DAM scenario were validated using inundation maps from 61 Sentinel-1 VV images obtained from 2020 to 2021. Since Sentinel-1 VV images were unavailable before 2015, the period of dam proliferation, validating NAT scenario inundation maps was impossible. We employed overall accuracy (OA) and Critical Success Index (CSI), which were derived from the confusion matrix, and calculated as:

$$\text{OA} = \frac{a + d}{a + b + c + d} * 100\% \quad (7)$$

$$\text{CSI} = \frac{a}{a + b + c} * 100\% \quad (8)$$

with a being true positive (water pixels correctly labeled), d being true negative (non-water pixels correctly labeled), b being false positive (water pixels incorrectly labeled), and c being false negative (non-water pixels incorrectly labeled). Since non-water pixels are dominant in the study area, the use of CSI helps avoid bias caused by an overwhelming volume of true negatives (Wing et al., 2017).

Table 2

Performance of the LSTM Model at Selected In Situ Water Level Stations During the Training and Testing Periods Which Were Split 70/30 From the Observed Period (1996–2021)

Station	RMSE (m)		R ²		NSE		KGE	
	Train	Test	Train	Test	Train	Test	Train	Test
Kompong Luong	0.32 (0.35)	0.60 (0.44)	0.98 (0.87)	0.98 (0.93)	0.98 (0.85)	0.93 (0.82)	0.98 (0.62)	0.82 (0.61)
Koh Khel	0.18 (0.19)	0.34 (0.29)	0.98 (0.92)	0.97 (0.94)	0.99 (0.90)	0.96 (0.89)	0.99 (0.60)	0.92 (0.57)
Chau Doc	0.22 (0.21)	0.23 (0.22)	0.97 (0.80)	0.95 (0.83)	0.96 (0.80)	0.90 (0.81)	0.92 (0.62)	0.82 (0.66)
Vam Nao	0.19 (0.18)	0.18 (0.18)	0.96 (0.76)	0.93 (0.80)	0.95 (0.75)	0.92 (0.80)	0.92 (0.67)	0.92 (0.73)

Note. The metrics in parentheses represent the models' ability to predict anomalies relative to the seasonal cycle.

4. Results and Discussion

4.1. The Skill of LSTM Models-Based Water Level Simulations

The HYPE-IROS model was previously validated using data from 58 gauged stations across 13 major river basins in the MRB and 29 gauged reservoirs (Du et al., 2020, 2022). Therefore, here we only showed the performance of LSTM models in simulating the downstream water levels, using four statistical metrics – RMSE, R², NSE, and KGE – by comparing the daily simulated water levels with observed data from 1996 to 2021. For each station, these metrics were reported for both the training and testing periods, which were split 70/30 from the observed period. Additionally, to isolate the model's predictive skill from seasonal variations, we also evaluated its performance in predicting anomalies. This was done by subtracting the seasonal component, calculated as the day-of-year average over the study period (1996–2021), from both the observed and simulated water levels.

Table 2 summarizes the performance of the LSTM water level models at the four stations. Overall, the models performed well across all metrics. RMSE ranged from 0.18 to 0.32 m during the training period and from 0.18 to 0.6 m during the testing period, with all stations achieving R², NSE, and KGE values above 0.8 in both periods. Examining the regime curve of the seasonal water level cycle in Figure 8, the model accurately captured the seasonal dynamics and interannual variability. However, it exhibited a slight overestimation/underestimation during the peak of the dry and wet seasons. This limitation in capturing certain extreme high and low water levels was also reflected in the water level anomaly metrics and time series comparison between LSTM-simulated and observed water levels (Figure S2 in Supporting Information S1). Compared to the prediction metrics of overall water levels, the water level anomaly metrics (shown in parentheses in Table 2) were slightly lower, with KGE generally above 0.6 and NSE above 0.75. This suggests that while the LSTM models performed well in predicting the seasonal water levels, they struggled with anomaly prediction, particularly for low water level anomalies (Figures S2c and S2d in Supporting Information S1). These higher errors in anomaly prediction could potentially lead to overestimation or underestimation of water extent in FIER inundation mapping. Future studies should focus on improving the model's ability to predict water level anomalies more accurately by incorporating additional ancillary data, such as tidal influences (Chang et al., 2019).

4.2. Dam Impacts on Hydrological Balance

To evaluate the impacts of dams on the hydrology of the LMB, we conducted a comparison of decadal water level averages (1982–2020) between two NAT and DAM scenarios. Table 3 presents the differences in maximum, minimum, and the mean water levels between DAM and NAT scenarios (i.e., DAM water levels minus the NAT water levels) in centimeters and percentages.

Since the 1980s, wet-season flows have consistently declined, whereas dry-season flows have increased, leading to corresponding decreases/increases in decadal average maximum/minimum water levels, respectively. The most drastic changes in water level minima and maxima occurred in the 2010s, ranging from a 2% – 5% decrease during the wet season and a 7% – 11% increase during the dry season. The drastic change in decadal average differences of the 2010s can be attributed to the operationalization of the majority of dams and reservoirs during this period, exacerbating the impacts on the hydrological balances of the LMB.

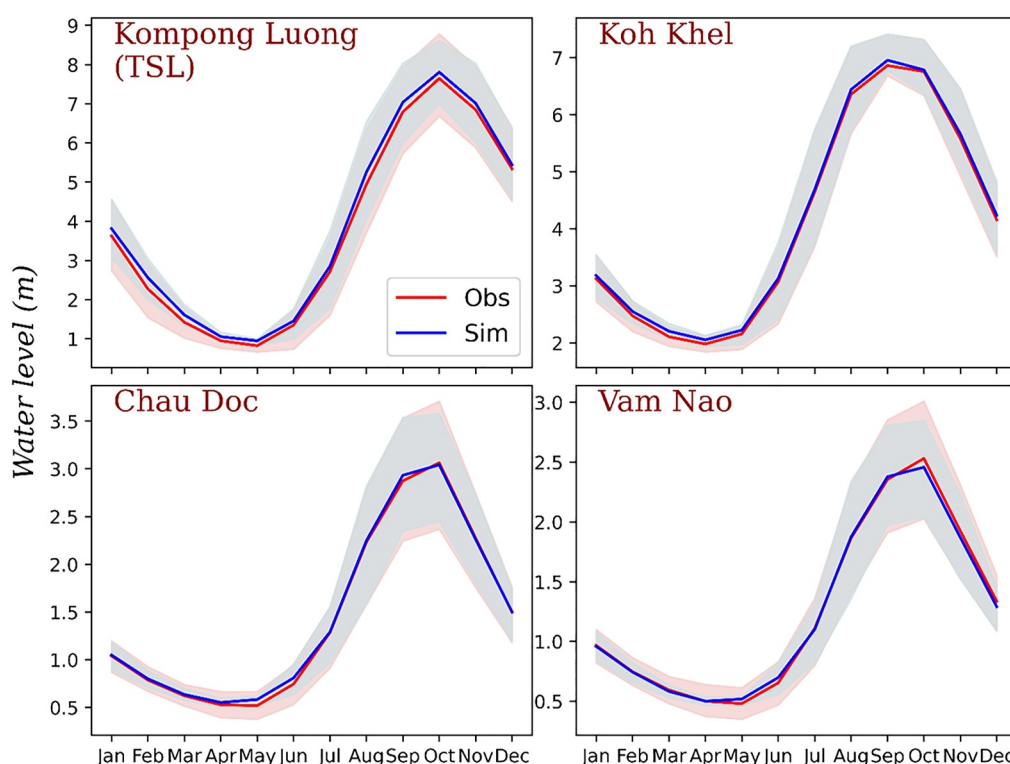


Figure 8. Regime curve and interannual variability (shading represents the upper and lower 25% quantile for each month) of simulated and observed water levels.

Minimal differences were observed for the water level means between the two scenarios. Since dams primarily redistribute water by storing it during the wet season and releasing it during the dry season, their overall impact on the region's water balance is minimal. These findings align with previous studies on dam-induced hydrological changes (Dang et al., 2022; Hecht et al., 2019) and are consistent with the expected effects of hydropower dams operations. Since dam operations tend to store more water during the wet season from abundant rainfall and release more discharge during the dry season to meet high energy demand (Fan et al., 2015), the existence of dams shifts water flows from the wet to dry seasons, contributing to the observed changes in the results.

4.3. The Skill of FIER-Based Inundation Mapping

To validate the inundation mapping skill of the framework, the inundation extent maps of DAM scenario were cross-compared with the inundation maps derived from 61 coincident Sentinel-1 VV images from 2020 to 2021. Given the absence of in situ inundation observation, this comparison served as a validation measure. Similar to the validation results reported in Chang et al. (2023), the mean overall accuracy (OA) was around 98%, and the Critical Success Index (CSI) score was about 78%. This level of accuracy is categorized as “fairly good” for flood forecasting (Bernhofen et al., 2018). The results, however, varied by month, with a considerable drop in skill during the wettest months of October and November (Figure 9).

The errors and uncertainties in the FIER methodology's inundation maps could be the result of multiple factors. Firstly, the uncertainties from the LSTM model-based water level prediction involving underestimation of water level peaks in the wet season, and from the NNR models used to derive RTPC values from the water levels. The uncertainties could propagate to the errors in FIER inundation extents, especially in the wet season. Secondly, similar to other data-driven approaches, FIER is limited by the extent and quality of its training data. While the approach can successfully simulate inundation extents in areas that were flooded during the 2017–2019 training period, new inundation locations that occurred in 2020–2021 but remained outside of the maximum inundation

Table 3
Decadal Average Differences in Water Levels Between the DAM and NAT Simulations (DAM–NAT)

Station	Decades	Max		Min		Mean	
		(cm)	%	(cm)	%	(cm)	%
Kratie	1980s	−8	−0.4	13	2	1	0.1
	1990s	−7	−0.4	12	2	1	0.0
	2000s	−18	−0.9	21	3	3	0.2
	2010s	−37	−2	64	9	16	1.5
	1984–2020	−20	−1	31	5	5	0.5
Kompong Luong	1980s	−5	−0.7	0.1	0.2	−2	−0.5
	1990s	−5	−0.7	−0.2	−0.2	−1	−0.4
	2000s	−4	−0.6	1	2	−2	−0.4
	2010s	−13	−2	5	7	−5	−1
	1984–2020	−7	−1	3	4	−2	−0.7
Koh Khel	1980s	−3	−0.4	−3	−1.7	−2	−0.6
	1990s	−2	−0.3	−0.8	−0.4	−1	−0.3
	2000s	−3	−0.4	2	0.7	−1	−0.2
	2010s	−12	−2	15	8	0.4	0.1
	1984–2020	−5	−0.7	4	2	−1	−0.2
Chau Doc	1980s	−4	−2	1	2	−1	−1
	1990s	−4	−2	1	2	−1	−1
	2000s	−4	−2	1	2	−1	−1
	2010s	−17	−5	6	11	−1	−1
	1984–2020	−7	−2	2	4	−1	−1
Vam Nao	1980s	−3	−1	0.4	1	−1	−1
	1990s	−3	−1	0.0	0.0	−1	−1
	2000s	−3	−0.5	0.5	1	−0.7	−0.5
	2010s	−12	−5	4	8	−1	−1
	1984–2020	−5	−2	1	2	−1	−1

Note. The most substantial differences in the maximum (red) and minimum (green) water levels are highlighted.

extent during the training period will not be accurately simulated. Nevertheless, since both the water levels under both DAM and NAT scenarios were simulated from the same LSTM models, these uncertainties would not impact the assessment of how hydropower dams and reservoirs affect the inundation dynamics of the LMB.

4.4. Dam Impacts on the Inundation Dynamics

To assess the long-term impacts of reservoirs and dams on the inundation dynamics of the LMB, inundation extents from 1982 to 2020 were generated for both the NAT and DAM scenarios. The inundation extent difference can be distinguished visually, especially during the most recent decade when dam-induced effects become more pronounced. Figure 10 provides a visual comparison of inundation extents between the two scenarios from 29 August to 1 September 2019. Visually, the decrease in inundation areas due to the presence of dams is apparent. While the inundated locations were relatively similar for both scenarios, the areas of inundation substantially reduced with the existence of dams (an average difference of approximately 560 km² in inundated areas between the NAT and DAM scenarios across the 4-day period).

Figures 11 and 12 depict the differences in dam-induced decadal inundation occurrence between the two scenarios, obtained by subtracting the NAT inundation occurrence from the DAM inundation occurrence during the wet (June–November) and dry (December–May) seasons, respectively. The decadal inundation occurrence was derived from daily inundation extent maps from 1982 to 2020 and represented the percentage of days that each pixel was inundated for each decade. During the wet season, the negative difference in the comparison between the DAM and NAT scenarios indicates that the existence of dams and reservoirs reduce the inundation occurrence in the LMB. While negligible distinctions can be observed during the first two decades of the study period, the last decade of the 2010s showed a drastic decline in inundation occurrence. Due to dams and reservoirs, the inundation occurrence during the wet season was significantly decreased at the outer periphery of the TSL and along the Cambodian floodplains by up to 6%, equivalent to 11 fewer inundated days per wet season. Compared to the Cambodian floodplains and TSL area, the Vietnamese Mekong Delta experienced a lesser impact from dams and reservoirs.

Differences in inundation occurrence during the dry season between the DAM and NAT scenarios showed a slight increase in inundation occurrence (i.e., increase in in-channel water) for the inner periphery of the TSL and the area near Chau Doc station. Similar to the wet season, the two scenarios exhibited similar patterns during the 1980s and 1990s, but notable differences emerged by the 2000s and 2010s, with up to 4% increase (equivalent to 6 additional inundated days per dry season). Since pixels with no inundation occurrence for both scenarios were masked out during the comparison, new pixel differences appearing since the 1980s suggest the emergence of new permanent and seasonal water pixels in the region, possibly influenced by the new dam development during the 2010s.

Differences in monthly inundated areas between NAT and DAM scenarios (Figure 13) exhibit the same trends as inundation occurrence and water level. The inundated areas shrank significantly during the wet season and expanded marginally during the dry season. During the dry season, the increase in dam-induced inundated areas was most prominent in January and February, with no significant difference observed for the March–June period. This is likely due to dams and reservoirs releasing stored water after the monsoon season at the beginning of the dry season. On the other hand, the decrease in inundated areas during the wet season predominantly occurred from August to October. Across the 39-year study period (1982–2020), the last decade exhibited the highest magnitude of differences, reaching up to +232 km² (+40%) during January and −664 km² (−6%) during September.

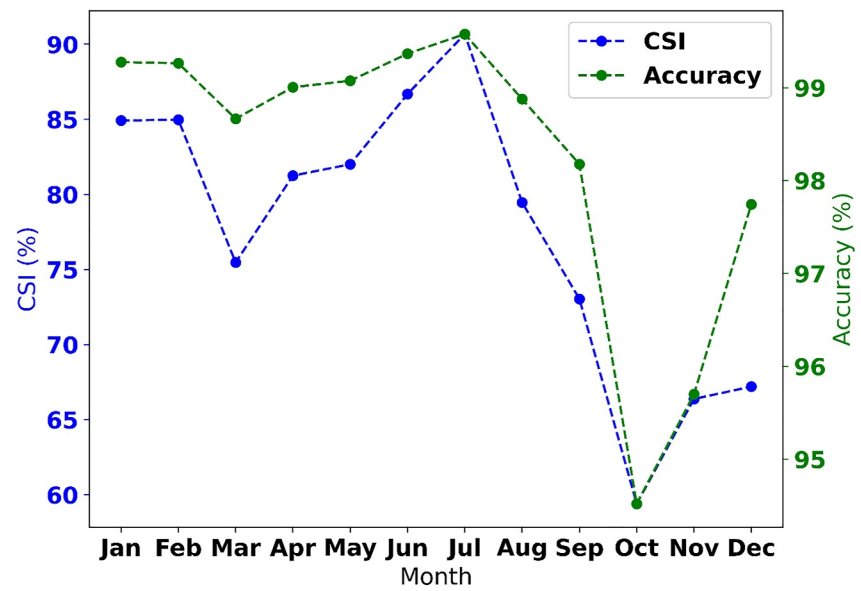


Figure 9. Monthly average of overall accuracy and CSI for FIER-generated inundation extent mapping.

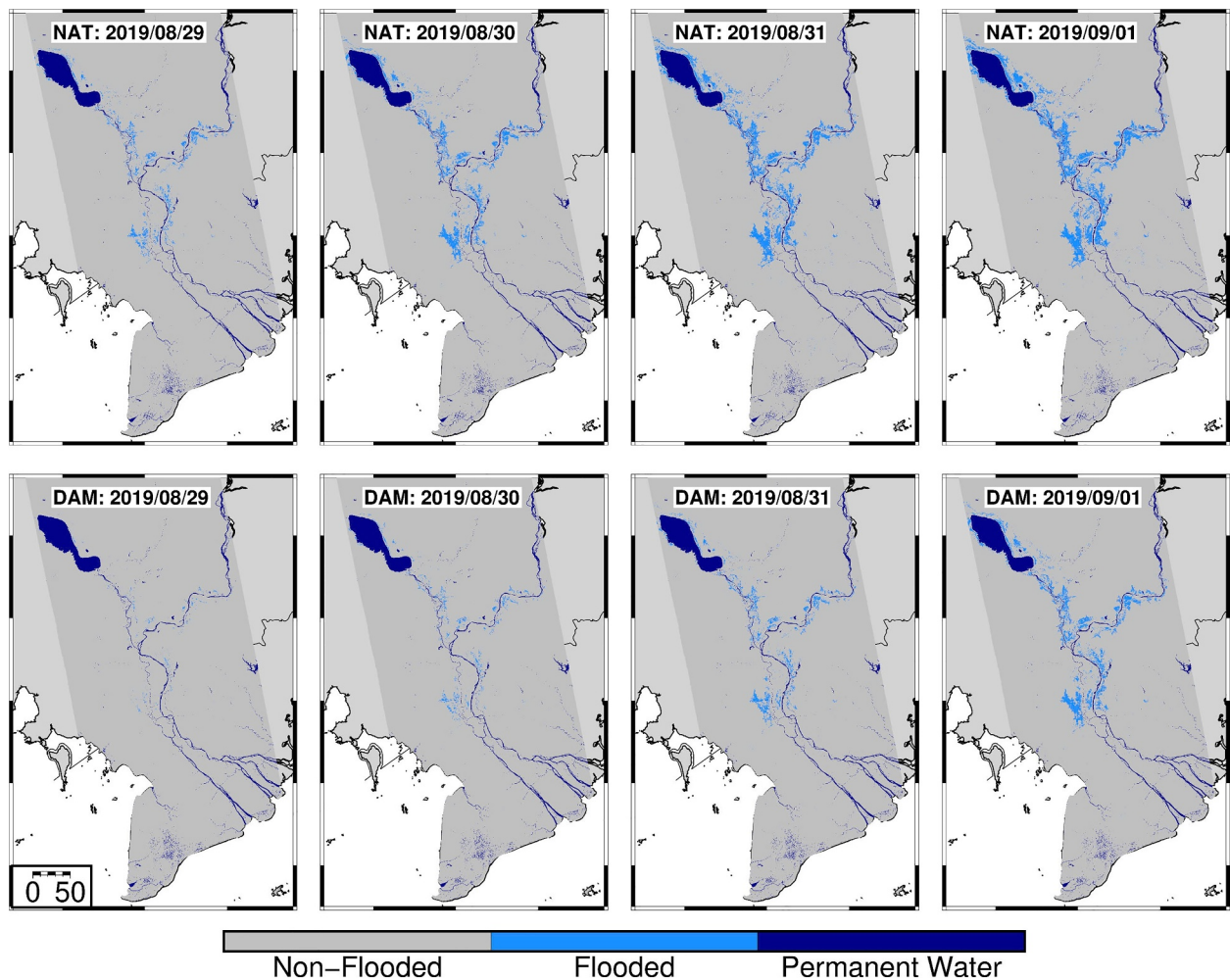


Figure 10. Inundation extent mapping for the NAT and DAM scenarios from 29 August to 1 September 2019.

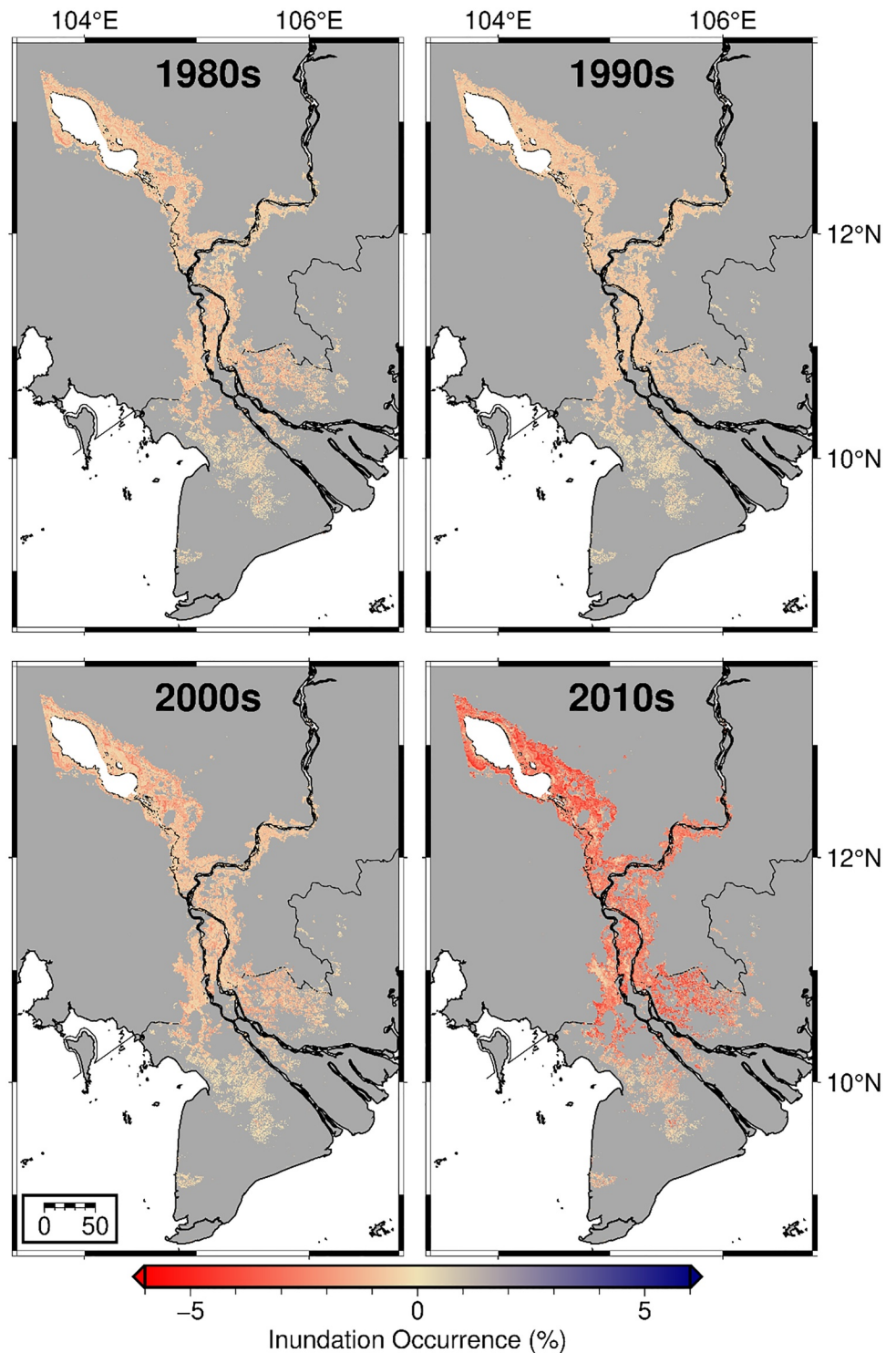


Figure 11. Decadal-average difference in inundation occurrence (%) between the DAM and NAT scenarios (DAM–NAT) during wet season (June–November).

The monthly inundated area difference result agrees with monthly water level difference between two scenarios, as illustrated in Figure 14, specifically depicting the monthly water level during the 2000s–2010s period for stations utilized in FIER inundation mapping. Results for the 1980s–1990s period can be found in Figure S3 of Supporting Information S1). Similarly, monthly water level difference between DAM and NAT scenarios was

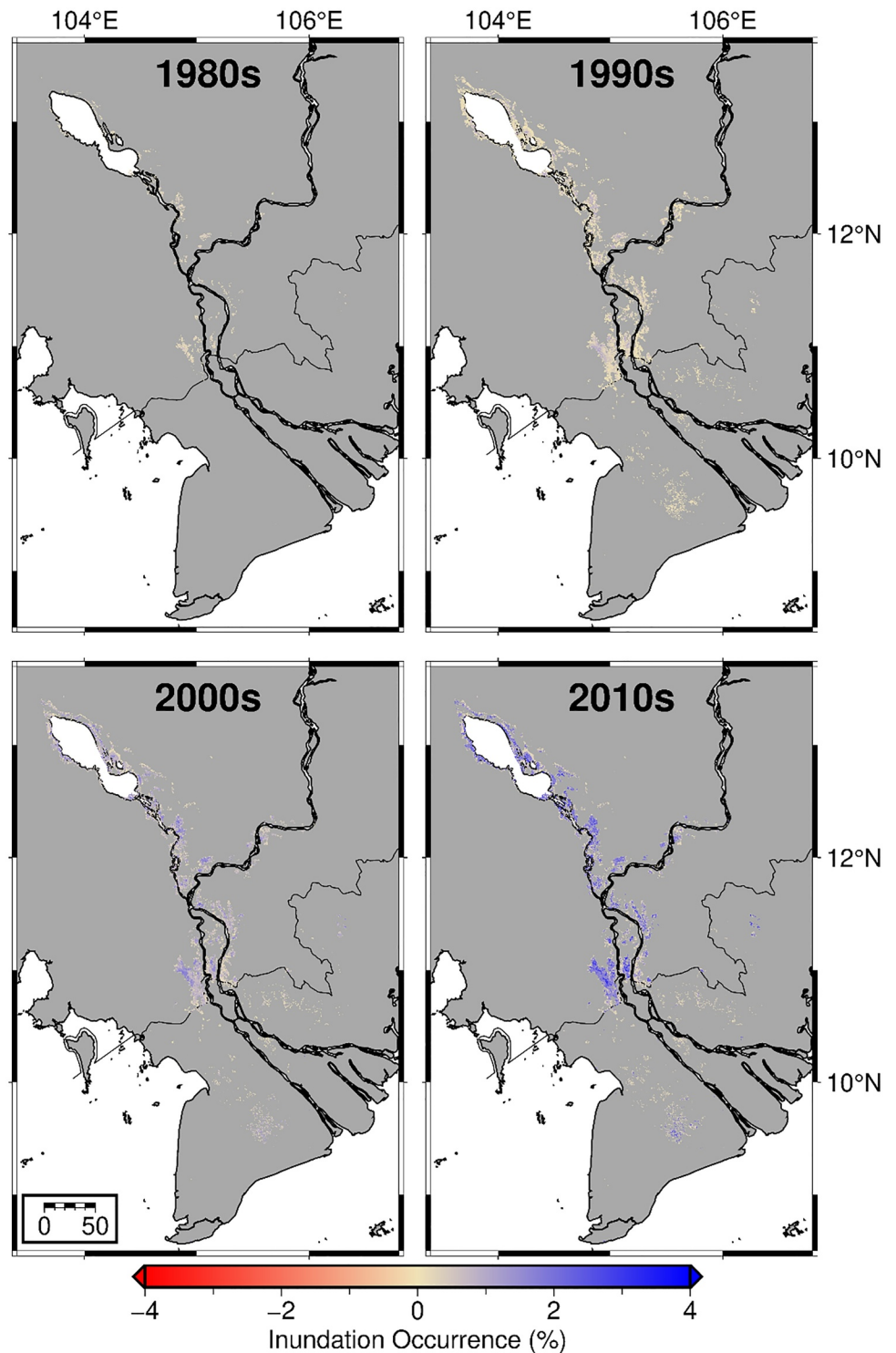


Figure 12. Decadal-average difference in inundation occurrence (%) between the DAM and NAT scenarios (DAM–NAT) during dry season (December–May).

most significant during the 2010s. During the wet season, the difference in water level was most notable during the August–October period, especially in Chau Doc and Kratie stations. On the other hand, while slight differences can be observed during the March–June period, water levels for both scenarios during these months were

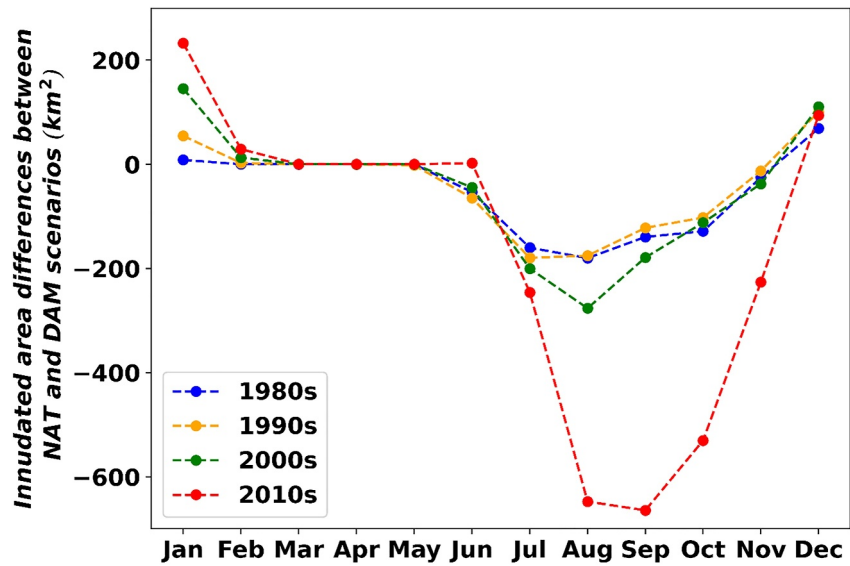


Figure 13. Decadal average difference in the inundated area (km^2) between the DAM and NAT scenarios (DAM–NAT) due to impacts of dams and reservoirs.

relatively lower compared to the January–February period, resulting in negligible inundated area differences during this period.

Over the last four decades, inundation occurrence and inundated area differences between the DAM and NAT scenarios have intensified over time during both dry and wet seasons. This escalation can be attributed primarily

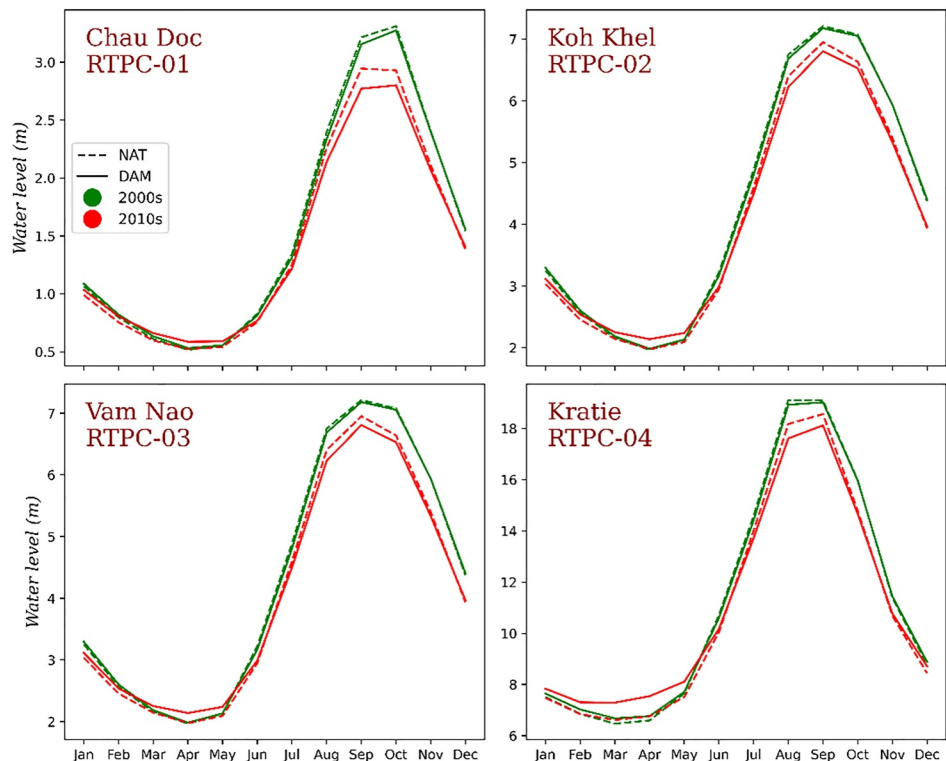


Figure 14. NAT and DAM monthly water levels (2000s–2010s) for stations that were coupled with RTPCs in the FIER framework.

to the increasing number of reservoirs constructed in the region. Thereby, it is expected that the future inundation dynamics of the LMB will be further influenced as more dams and reservoirs are planned for development in the region.

4.5. Discussion

To assess the hydrological impact of hydropower dams on water levels and inundation dynamics, here we have proposed a framework that combines the satellite data-driven FIER method, and process-based hydrological model HYPE that includes the integrated reservoir operation scheme. The resulting water levels and inundation extent maps of the Lower Mekong River basin (LMB) were generated for the period of 1982–2020 for the two scenarios of NAT and DAM. By comparing the water levels and inundation changes between the DAM and NAT scenarios, we can discern the substantial impacts of dams and reservoirs on the hydrology of the LMB.

In general, the existence of dams in the LMB is found to increase/decrease water levels and inundation areas and occurrences during the dry/wet seasons, respectively. While dam-induced effects are relatively minor in the first three decades, substantial differences between NAT and DAM scenarios can be observed in the 2010s. During the 2010s, when dam-induced effects are the most prevalent, water levels across the region experience approximately a 2% – 5% decrease during the wet season and a 7% – 11% increase during the dry season. In terms of flood dynamics, a decrease in inundation occurrence during the wet season is found mostly around the outer periphery of the TSL and on the Cambodian floodplains due to the lower gradient in these areas which make them more susceptible to flooding. During the dry season, an increase in inundation occurrence can be observed around the inner lake body of TSL and near Chau Doc station in Vietnam. In addition, while a consistent increase in the magnitude of dam-induced impacts can be observed across the region, the most downstream areas of the LMB, such as the Vietnamese Mekong Delta, experience a somewhat smaller magnitude of dam-induced changes compared to the rest of the region. As flood prevention infrastructures, such as drainage systems, floodwater discharge canals, sluice gates, and protection dikes, have been constructed for the delta for agriculture purposes (Hoang et al., 2018), negligible flooding in the area was observed from the SAR images during the FIER training period of 2017–2019. Since the framework relies on the flooding events during the training period, both scenarios NAT and DAM also exhibit little inundation extent in the area. This results in fewer inundation difference pixels in the Vietnamese Mekong Delta, as shown in Figure 11. Additionally, the diminished impacts observed in the Mekong Delta may also stem from other factors, such as the presence of dykes and sand mining activities (Park et al., 2020; Triet et al., 2017). However, since the FIER training period coincides with a time when dyke construction in the region had largely saturated (Vo et al., 2020), the impacts of dykes have been indirectly isolated, ensuring that the findings are not significantly affected by dyke infrastructure. When replicating this framework in other poorly gauged regions, it is crucial to carefully select the FIER training data set to minimize the influence of dyke impacts. Although our current framework does not explicitly consider or assess the specific impacts of downstream modifications on inundation dynamics, it offers a viable alternative approach for evaluating upstream alterations, such as dam operations and land cover changes.

These results suggest that hydropower dams and reservoirs alter the region's hydrological balance, in particular by weakening the seasonal fluctuations of inundated areas and occurrence in the region. As many fishing communities and agriculture activities in the region reside in areas with the strongest effects of dams on inundation dynamics (Figure 2), these dam-induced impacts will have significant implications for fisheries and agriculture activities in the region in various timescales. On a short-term scale (1–5 years), the alteration of flow and flood dynamics (timing, extent, and duration of seasonal flood) in the floodplain due to hydropower dam development can be devastating for habitats (Baran et al., 2003; Intralawan et al., 2019; Sabo et al., 2017). In the MRB, especially the LMB, fishing habitats rely on the monsoon rains that drive a flood pulse throughout the basin to create floodplains for spawning, feeding, nursing, and migration. The dam-induced decreases in seasonal inundation occurrence and inundated areas can potentially impose damaging effects on “mean body size, fecundity, survival, and ultimate catches” of fishes (Halls & Hurtle, 2021). Secondly, since the seasonal flood surges also bring necessary nutrient-rich sediments and freshwaters (Intralawan et al., 2019; Sabo et al., 2017), the blockage and alteration of flow and flood pulse by hydropower dams and reservoirs, along with their trapping of natural river-borne sediment, can adversely affect the ecological well-being and biodiversity of the alluvial plains in Cambodia and Vietnam (VMNRE, 2015; Yoshida et al., 2020). Lastly, hydropoaking, which refers to the abrupt release of water retained in the storage reservoirs to meet unusually high energy demand during daytime/summer, also has a negative effect. Specifically, it reduces reproductive output and disrupts the upstream migration of adult

fishes (Arias et al., 2014; VMNRE, 2015). Indeed, surveys of fishers and villages in the MRB in the last decades have reported significant decreases in fish population and body sizes (Campbell et al., 2020; Ngor et al., 2018). On a medium to long-term scale (over years to decades), these impacts from dams and reservoirs can lead to changes in population dynamics and genetic shifts as species either adapt to new conditions or migrate away (Oliveira et al., 2018; Wolf et al., 2022). These negative influences of large impoundment and flow regulation by dams and reservoirs on fisheries and ecosystems have been cautioned and observed in other large river basins worldwide (Santos et al., 2018; Winemiller et al., 2016), and the MRB, unfortunately, appears to head toward the similar trajectory.

For agriculture, while some areas can become less flood-prone and will potentially be suitable for irrigated agriculture and tree crops, the dam-induced water level increases in the dry season can also affect the arable land availability in the region (Keskinen et al., 2015). Indeed, other impacts on agriculture due to hydropower development such as increasing salinity and reduction of sediment flows and water quality have been found to lead to a net negative of 2.3% decrease in rice production in Vietnam and 3.7% in Cambodia (VMNRE, 2015). While hydropower development undeniably provides benefits in energy production, these trade-offs between electricity generation and food security and environmental impacts are certainly questionable (Intralawan et al., 2019; Ziv et al., 2012). Although the abundance of future planned dams and reservoirs in the MRB indicates that hydropower is perhaps unavoidable in the region, investigations on reservoir operation rules, future planning, and their environmental impacts must be thoroughly conducted for the well-being of the MRB's social-ecological systems and local communities.

The results from our FIER-HYPE-IROS framework concur with those from previous studies using the hydrodynamic modelling (Chua et al., 2022; Dang et al., 2022; Pokhrel, Shin, et al., 2018) and help quantify the hydrological impacts of hydropower dams on water levels and inundation dynamics in the LMB. To overcome the uncertainty from backwater and tidal effects, which impact both hydrological and hydrodynamics modelling, in simulating the Mekong Delta water levels, we employ the LSTM modelling to derive downstream water levels in the LMB from upstream simulation from HYPE and obtain prominent results when being compared to in situ data. The FIER-HYPE-IROS framework is thus effective in analyzing changes in downstream inundation extents resulting from dam operation. It offers a cost effective alternative to the existing methods for assessing dam impacts on inundation dynamics, particularly at poorly gauged and ungauged basins where detailed input data for complex hydrodynamics models is lacking. By relying mostly on remote sensing and publicly available data, FIER-HYPE-IROS helps isolate and evaluate the impacts of hydropower dams on the natural hydrological balance and inundation dynamics. Additionally, the framework has the potential to complement the current FIER operational flood inundation system (Chang et al., 2023), allowing for quantitative isolation of impacts from individual dams or groups of dams and reservoirs.

Nevertheless, the framework, like every other model, has its own uncertainties and limitations. The FIER-HYPE-IROS contains uncertainties stemming from errors in each component of the framework. First of all, although the GM-HYPE model has shown satisfactory results, it can still suffer from uncertainties due to its forcing data and regional/climate attributes. For instance, the merged precipitation product GM-FORCE used in the model is vulnerable to underestimation of peak rainfall and tends to fail at predicting no-rain days due to the weighted-averaging scheme of multiple data sets (Beck et al., 2019). Therefore, the errors from precipitation forcing data can propagate into the HYPE model and contribute to the model uncertainty. Additionally, this analysis does not account for the impact of reservoir sedimentation on storage capacity, which could influence water level simulations across the scenarios. However, since most reservoirs became operational after 2010, the effects of sedimentation are relatively minor. In addition, the water levels at downstream stations, as estimated by the LSTM models, carry a certain degree of error, since they struggled with anomaly prediction.

For the FIER component, as mentioned earlier, the errors in inundation mapping result from uncertainties in GM-HYPE and LSTM's water level simulations, as well as in the water level-RTPC regression models. The current FIER version simulates predicted RTPC using coincident water levels and REOF-derived RTPC but struggles to differentiate between rising and receding floods due to its lack of consideration for previous water level conditions. Since recent changes in water levels can significantly affect current inundation conditions, using coincident water levels may limit the model's ability to capture the full hydrological patterns necessary for accurate inundation simulation. Additionally, since FIER relies on historical flood events during the Sentinel-1 observation window (2017–2019) as training data, it may underestimate more extreme flood events occurring outside

of that period. For example, new seasonal inundation areas that occurred during the 2020–2021 period (shown in Figure S4 of Supporting Information S1) would potentially be misclassified as non-water by FIER if the pixels were never flooded during the training period. This limitation could be mitigated by using training data sets with longer duration from different sources of satellite images. Furthermore, since our current framework is currently designed to evaluate upstream alterations on inundation dynamics, it should be used with caution when active downstream modifications are present in training data sets of FIER model. Future studies should explore methods to incorporate the impacts of downstream alterations, such as dykes and sand mining, into the framework.

4.6. Future Work and Application

Due to the rapid expansion and planning for more dams and reservoirs in the tributaries of the Mekong region, it is crucial to assess the impact of new dams on the hydrological regimes and inundation dynamics of the MRB. In the future, we aim to include a comprehensive list of dams under construction and in planning phases, enabling a thorough assessment of potential impacts of future dams. Furthermore, more elaborate scenarios with different sets of cascading dams can be explored, including distinguishing between impacts attributed to dam locations, such as main stem dams and tributary dams. This exploration will help determine which dam locations or specific reservoirs have the greatest influence on hydrological changes. By incorporating such comprehensive assessment, we can better inform decision makers and stakeholders about mitigation and adaptation measures regarding reservoir impacts, such as the optimal distribution of dams. This will aid in sustainable water resources management, conservation efforts and livelihood protection.

In our framework, IROS relies on basic reservoir information (e.g., total storage capacity, geographic location) and remote sensing images to estimate reservoir Area-Elevation-Volumes and operation rule curves that are not always accessible. FIER assists in simulating water extent maps in regions with limited river bathymetry and high-resolution DEM. Hence, the proposed FIER-HYPE-IROS can be applied to other poorly gauged basins where public rule curves and in situ data are limited, leveraging satellite imagery for remote monitoring.

Further research should address the significant impacts of dams and reservoirs on sedimentation by examining dam-induced effects on sediment and nutrient transport across the region. The HYPE model's capability for simulating sediment transport and sedimentation (Bartosova et al., 2021; Bui et al., 2023) suggests that integrating it with the existing framework could help quantify more comprehensively impacts of dam operation and sedimentation on inundation dynamics in the LMB.

Future improvements to the FIER approach will include incorporating both historical and current water levels to better capture hydrological patterns and enhance inundation extent simulations. Additionally, future studies should explore methods for integrating the impacts of downstream modifications, such as dykes, into the framework. The FIER framework can also be adapted to utilize sediment maps derived from optical imagery for hindcasting and forecasting sediment concentrations across the Mekong floodplain delta, influenced by upstream dam operations. This comprehensive approach will improve our understanding of the complex interactions between dams, inundation, and sediment dynamics, ultimately leading to more effective water management strategies in the region.

5. Conclusion

In this study, we propose the FIER-HYPE-IROS framework, a data-driven, remote sensing-hydrological modeling hybrid approach for analyzing dam impacts on inundation dynamics. The framework provides a cost-effective alternative to existing approaches that rely on historical observations (i.e., in situ hydrological data, satellite imagery) or on physical models, especially in poorly gauged regions with limited data access and model calibration resources. By primarily using remote sensing data, our approach can greatly benefit local stakeholders and decision makers in poorly gauged or even ungauged basins. We applied the FIER-HYPE-IROS framework over the Lower Mekong River basin (LMB) to assess the long-term effects of dams and reservoirs on basin-wide inundation dynamics. As the LMB is home to the largest freshwater fishery and is a major rice exporters, understanding how hydropower development affects the region's hydrological balance and inundation dynamics is crucial for informed decision-making and sustainable development.

Our objectives were to build and evaluate water levels and inundation maps for two scenarios: one without dam and one with dam. Using the FIER-HYPE-IROS framework, we simulated the 39-year-long (1982–2020) of

water level data, and generated daily inundation extent maps for both scenarios in the same period. Assessment of the differences between the two scenarios provided insights into the long-term effects of hydropower development on natural flows and flood dynamics of the LMB. The dam-induced effects were primarily characterized by a shift in water volume from the wet to the dry season. Dam operations typically store water during the wet season and release it during the dry season, resulted in consistent increases/decreases of water levels, inundation occurrence, and inundated areas in the LMB during the dry/wet season throughout the study period. The most significant changes occurred during the 2010s, when the majority of dams became operational. Key findings for this period include:

1. A 2% – 5% water level decrease during the wet season and a 7% – 11% water level increase during the dry season;
2. Up to a 6% (11 days/wet season) decrease and 4% (6 days/dry season) increase in inundation occurrence during the wet and dry seasons, respectively;
3. Up to a 6% (664 km²) decrease and a 40% (+232 km²) increase in monthly average inundated area during the wet and dry seasons respectively;
4. Spatial variations, with wet season effects predominantly observed in lower gradient areas and negligible dam effected noted in the Vietnamese Mekong delta.

These findings highlight the spatiotemporal complexity of the dam impacts in the LMB. As flooding and water availability are critical for fisheries and agriculture in the region, the growing number of hydropower dams and reservoirs in the LMB and their associated hydrological impacts pose on-going concerns for the social-ecological systems and local communities dependent on the Mekong River.

Our framework produced results comparable to those of existing studies using coupled hydrological-hydrodynamic models (Dang et al., 2022; Pokhrel, Shin, et al., 2018; Shin et al., 2019). The proposed FIER-HYPE-IROS framework has several advantages, including significantly lower computational and data input requirements, as well as easy access to remote sensing data as input, which greatly benefit poorly gauged regions like the LMB. However, our approach suffers from the uncertainties from each component of the framework, such as limitation in predicting water level anomaly relative to the seasonal cycle, difficulties in predicting new water pixels outside of the training period, and the choice of regression models in predicting temporal component of FIER. Additionally, it does not account for downstream hydrological alterations like sand mining and dykes. Despite these challenges, FIER-HYPE-IROS can certainly serve as a cost-effective and scalable tool for assessing upstream hydrological modifications, such as dam operation or land use changes, on downstream inundation dynamics in poorly gauged basins. Future studies will address these limitations to enhance the framework's benefits and mitigate its drawbacks.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Ancillary data on land use change in the Mekong delta was obtained from Vu et al. (2022). The HYPE source code is available from <https://sourceforge.net/projects/hype/files/>. To view the near-real-time inundation forecasting results produced by the FIER application in the Lower Mekong River basin, visit <https://fier-mekong.streamlit.app/>. Additionally, the source code and key results for this application can be found at Lee (2024): <https://doi.org/10.5281/zenodo.13892283>.

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