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Estimating water levels and discharges in tidal rivers and estuaries: Review of machine learning approaches

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ABSTRACT

Understanding the dynamics of tidal rivers and estuaries is critical for reliable water management. Recently, the use of Machine Learning (ML) has increased in favor of hydrologic and hydraulic models. The advantages of ML over physically based models are most evident in modeling complex and nonlinear hydrologic processes and inverse problems. This study provides a critical review of ML approaches for forecasting, reconstruction, and establishment of stage-discharge relationships in tidal rivers and estuaries characterized by nonlinear interaction between the river and coastal processes. Gaps in this research area and the limited number of stage-discharge studies are identified and explained. The advantages and limitations of each approach are discussed from a critical perspective, and suggestions are made for future research directions. Advanced Recurrent Neural Networks (RNNs) and hybrid modeling systems combining physically based models with ML appear to be the most promising approaches for modeling complex physical processes in these environments.

1. Introduction

Tidal rivers and estuaries are an important and vulnerable part of the human ecosystem. Various natural disasters, such as floods and droughts, as well as human activities, negatively affect these environments (Chen et al., 2020; Hosseiny, 2021). Climate change, urbanization, and migration trends are likely to exacerbate extreme weather events, highlighting the critical need for water and coastal management plans to protect water security, economies, and public health (Pörtner et al., 2022). One of the most noticeable consequences of ongoing climate change is sea level rise, but changes in the frequency and intensity of extreme events, including storm surges and river flows, are also noticeable (Pörtner et al., 2022). Water management plans are constantly evolving, with a focus on preventing, mitigating, and preparing for water-related risks. Therefore, accurate and reliable monitoring, modeling, and forecasting systems are essential for the sustainability and protection of tidal rivers and estuaries.

Hydrologic research aimed toward tidal rivers and estuaries has improved in recent years through the use of data-driven approaches, particularly machine learning models (ML) (Hidayat et al., 2014; Wei, 2015; Guo et al., 2021). Traditionally, two main modeling approaches have been used: (a) physically-based hydraulic models (Sivakumar et al., 2002), and (b) conceptual hydrologic models (Wei et al., 2012). While hydraulic models simulate physical processes by solving complex differential equations (Chau, 2006b), hydrologic models provide a simplified representation of these laws (Sit et al., 2020; Zounemat-Kermani et al., 2020).

The main advantage of hydraulic and hydrologic models compared to ML is the ability to understand the physical mechanisms (Sivakumar et al., 2002; Zaherpour et al., 2019). However, these benefits come with numerous limitations. High computational costs (Zhang et al., 2016) and mandatory model calibration (Zhang et al., 2016; Guo et al., 2021) are just some of the potential problems. Other challenges specific to tidal rivers and estuaries include long-term data needs for tidal analysis (Zhang et al., 2016), expensive or inaccessible field monitoring (Tauro et al., 2018), complex nonlinear interaction between tides and river flows (Hidayat et al., 2014), inability to account for all relevant meteorological factors (Zhang et al., 2016), highly dynamic processes (Chang and Chen, 2003), and the need for continuous, high-resolution water level and discharge data to define boundary conditions (Bhar and Bakshi, 2020). Despite their complexity, these traditional models may not always accurately represent natural processes due to nonlinear interactions between tides, waves, river flow, temperature, water density, and river geometry (Tazin et al., 2019). Furthermore, standard hydraulic models cannot be applied directly for inverse hydraulic problems (identification of unknown flow conditions

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or fluid properties based on an observed free surface response), and must be combined with other approaches (Sellier, 2016).

On the other hand, simple statistical models, such as Auto Regressive (AR), Moving Average (MA), Auto Regressive Moving Average (ARMA), Auto Regressive Integrated Moving Average (ARIMA), Linear Regression (LR), and Multiple Linear Regression (MLR) have been used for water level and discharge prediction since 1970 (Valipour et al., 2012, 2013; Valipour, 2015). However, these models struggle to capture the nonstationary and nonlinear processes specific to tidal rivers and estuaries.

Machine learning offers a powerful alternative to physical-based models and improves simple statistical approaches by achieving better performance and increasing overall accuracy (Zounemat-Kermani et al., 2020). ML models can be further enhanced by combining them with other computational techniques to create hybrid models (Nourani et al., 2014). The idea of hybrid models is to combine ML with optimization techniques, signal processing, statistical methods, preprocessing, or physical understanding of the underlying processes. Additionally, different ML methods can be combined for improved efficiency (Zhang et al., 2023a).

Numerous studies have demonstrated the effectiveness of ML for simulating hydrologic and hydrodynamic processes (Oyebode and Stretch, 2019; Zounemat-Kermani et al., 2020). ML methods have been successfully applied to diverse hydrological problems, including flood forecasting (Mosavi et al., 2018; Zounemat-Kermani et al., 2020), groundwater level estimation (Rajaee et al., 2019), water resources management (Sit et al., 2020), dams and reservoir management (Allawi et al., 2018), sediment transport prediction (Afan et al., 2016; Rajaee and Jafari, 2020; Zounemat-Kermani et al., 2020), water temperature prediction (Zhu and Piotrowski, 2020), water quality modeling (Chau, 2006a; Tung et al., 2020), sewer flow modeling (Zounemat-Kermani et al., 2020), and more. A key advantage of ML is its ability to describe the spatio-temporal variability of complex inputs without requiring a complete description of the underlying physical process (Zhou et al., 2020). Additionally, ML approaches are well-suited for understanding and describing nonlinear relationships between inputs and outputs (Guo et al., 2021).

Several review studies have explored ML for water level and streamflow forecasting or reconstruction. Yaseen et al. (2015) reviewed studies (2000–2015) on artificial intelligence (AI) for streamflow modeling and forecasting in rivers. Zhang et al. (2018) compared data-driven models for short-term streamflow forecasting, particularly relevant for data-scarce regions. Hamzah et al. (2020) reviewed deterministic imputation methods and ML approaches for streamflow reconstruction. Zhu et al. (2020) reviewed ML models for lake water level forecasting, discussing advantages, limitations, and efficacy for these highly stochastic and nonlinear processes. Wee et al. (2021) provided a similar review for reservoir water level forecasting using ML models. Finally, Ibrahim et al. (2022) reviewed hybrid ML approaches (2009–2020) for hydrological streamflow forecasting in rivers, reservoirs, and lakes.

While these review studies on ML approaches for water level and streamflow forecasting cover freshwater environments, including rivers, reservoirs, and lakes, a systematic review specifically aimed at tidal rivers and estuaries remains absent. Unlike inland systems with relatively predictable flows and homogeneous salinity, tidal rivers and estuaries experience a dynamic interplay between freshwater flow, saltwater intrusion, and tides. This results in salinity gradients, turbulent mixing zones, and complex flow regimes. Therefore, coastal studies require higher temporal resolution (hourly scale) to capture these interactions compared to daily or monthly scales often used for inland water systems. Existing reviews on inland water systems (Yaseen et al., 2015; Zhu et al., 2020; Wee et al., 2021; Ibrahim et al., 2022) confirm this distinction, with the majority of studies using daily, weekly, or longer time frequencies.

A lack of reviews of ML approaches for tidal rivers and estuaries highlights a crucial knowledge gap. This review aims to address this gap by providing:

- A comprehensive examination of ML approaches for water level and discharge assessments in tidal rivers and estuaries.
- A critical evaluation of current methodologies and discussion of their advantages and limitations.
- Suggestions for future research directions to enable potential improvements.

By shifting the focus from inland water systems to complex coastal environments, this review offers novel insights into the full potential of ML approaches for coastal water management, specifically for water level and discharge estimation in tidal rivers and estuaries. This knowledge can enhance the sustainability of water management practices, improve preparedness for natural disasters, and ultimately create a more resilient coastal infrastructure.

The remainder of the paper is organized as follows. Section 2 describes the importance of hydrological parameters — water levels and discharges. Section 3.1 details the selection process of relevant studies. Section 3.2 presents a classification of the various ML approaches used for hydrologic processes in tidal rivers and estuaries. Sections Section 3.3, 3.4, and 3.5 summarize studies on developing and applying ML for forecasting, reconstruction, and establishing stage-discharge relationships, in three phases, as pioneering work, early applications, and recent advancements. Section 4 addresses the shortage of existing studies for solving the mentioned problems for specific periods and discusses the reviewed ML models according to their advantages and limitations. The final section summarizes the entire study, provides the main conclusions, identifies knowledge gaps, and offers suggestions for future research and improvements.

2. Hydrological parameters in tidal rivers and estuaries

Tidal rivers and estuaries are influenced by multiple forcing mechanisms that have different natural sources. External influences from the sea (sea levels, tides, waves), land (river flow), and the atmosphere (precipitation, winds, pressure) interact with internal water properties (temperature, salinity) and channel morphology (Geyer and MacCready, 2014). In addition, all of these parameters may become variable and nonstationary over longer periods of time as a result of climate change (Pörtner et al., 2022). Because of the multiple influencing factors, hydrologic processes in tidal rivers and estuaries are considered nonlinear, complex, and challenging to model (Chen et al., 2012; Gan et al., 2021). Therefore, selecting appropriate modeling approaches that consider the specific characteristics of each environment is crucial.

An example of the hydrologic parameters of the Neretva River, Croatia, is shown in Fig. 1. This figure shows a time series of measured water levels at three stations along this salt-wedge estuary (near the river mouth, at Opuzen station, located 11.75 km upstream from the mouth, and at Metković station, located 20.65 km upstream from the mouth). The measured data have a temporal resolution of one hour. This figure illustrates the effects of tidal waves propagating 20 km upstream, as well as the interaction between tidal dynamics (primarily noticeable as inter-daily oscillations) and river discharge (characterized by a seasonal variability) in the middle part of the estuary (Krvavica et al., 2021a).

This review focuses on two key hydrological parameters: water levels (river stage) and discharges (streamflow, flow rate), and their dynamic response to both freshwater inflows and tidal forcing. Each parameter serves a distinct purpose in hydrological analysis. Water levels are crucial for flood forecasting and warning systems, while discharges are often the primary variable for developing predictive or reanalysis models (Yu et al., 2006), water resource evaluation (water supply, irrigation), and controlling processes within river ecosystems (Doyle et al., 2005).

2.1. Water levels in tidal rivers and estuaries

Water level, also known as river stage, is a crucial indicator for understanding river dynamics (Ghorbani et al., 2016). Water level

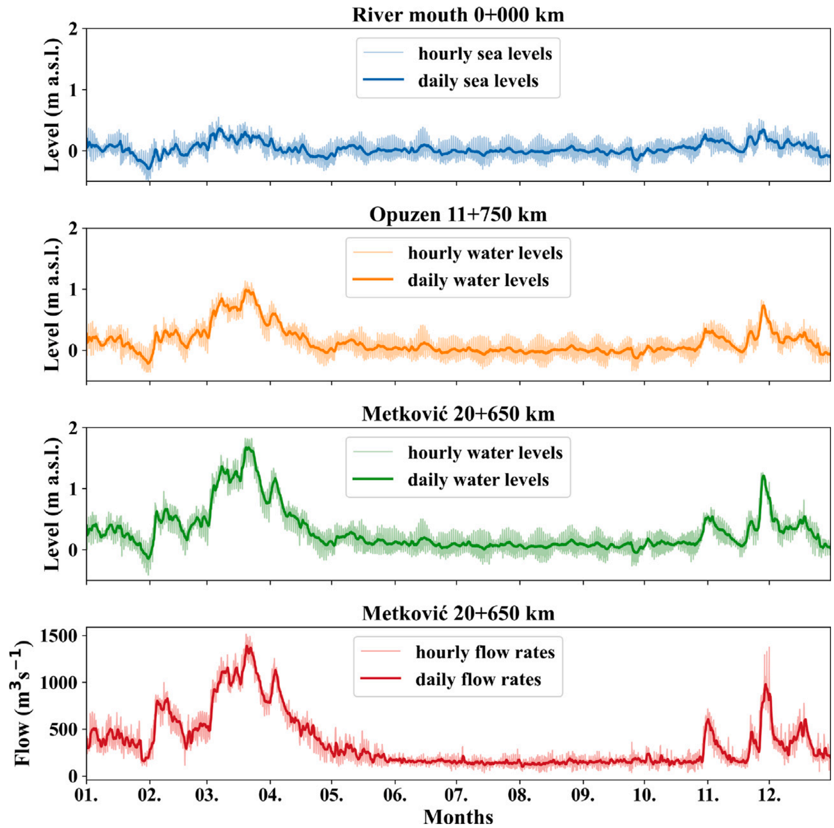

Fig. 1. Example of water level and flow rate time series measured at the river mouth, station Opuzen (11.75 km from the mouth), and station Metković (20.65 km from the mouth) in the Neretva River, Croatia. Modified from (Krvavica et al., 2021b).

estimation is critical for predicting extreme events like floods (Gan et al., 2021). Most commonly, the water level parameter is used for flood warning systems (Yu et al., 2006).

Water level is typically measured at gauging stations along a river and reflects the height of the water surface relative to a pre-established reference level. Various instruments are used for this purpose, including water level gauges, pressure sensors (Sauer and Turnipseed, 2010), radars, and satellite altimetry data (Tauro et al., 2018).

Predicting water level variations is relatively straightforward in river sections outside the tidal limit. However, tidal rivers present a significant challenge due to the complex interaction of tidal wave dynamics with river flow (Chen et al., 2020). The propagation of tidal waves is affected by the shallow water effect (Chen et al., 2020) and further modified by the channel geometry and the nonstationary streamflow, further complicating modeling efforts (Supharatid, 2003a; Chen et al., 2020, 2012). The propagation of salt-wedge in highly-stratified estuaries also significantly modifies the water levels along the river channel (Krvavica et al., 2021a). In addition, limited accessibility in some locations can pose challenges for water level measurement (Bhar and Bakshi, 2020).

2.2. Discharges in tidal rivers and estuaries

Discharge, also known as streamflow or flow rate, is another crucial factor in tidal rivers and estuaries. It reflects the general response of the watershed (hydrologic processes) and the attenuation of flow (hydraulic processes) (Ghorbani et al., 2016). Unlike water level, discharge cannot be directly measured using ground-based instruments or satellite sensors. Therefore, it is typically estimated based on directly measured parameters like water depth and flow velocity (Tauro et al., 2018).

The simplest and least expensive method for estimating river discharges are Rating Curves (RC), which define a functional dependence between river level and discharge at a given channel cross-section based on individual flow measurements (Jones et al., 2019). However, RCs become unreliable in tidally influenced sections due to the complex interaction between river discharge, downstream sea level, and propagating tidal waves, leading to a nonlinear relationship between water level and discharge (Cai et al., 2014; Jones et al., 2019). While non-tidal river level data can be used to estimate downstream discharges, such methods can be inaccurate, especially in lowland systems where saltwater intrusion and tidal influence can extend 10–100 km inland (Geyer and MacCready, 2014; Krvavica et al., 2021a).

The most reliable method for continuous measurement of discharge in estuaries and tidal rivers involves fixed acoustic instruments (Hoitink et al., 2009; Sassi et al., 2011), typically Horizontal Acoustic Doppler Current Profiler (H-ADCP) (Garel and D'alimonte, 2017), which is a reliable but costly approach. However, under stratified conditions, interpolation of measured velocities across the channel cross-section provides absolute flow rate rather than river discharge (Krvavica et al., 2021b). Therefore, this has led to the recent exploration of ML models for discharge estimation (Hidayat et al., 2014).

3. Overview of machine learning approaches

3.1. Selection of relevant studies

Web of Science (WoS) database served as the primary search engine to identify relevant studies on developing or applying machine learning for modeling water levels and discharges in tidal rivers and estuaries. Keywords were chosen based on relevant hydraulic parameters (various technical terms used for *water level* and *discharge*), area of study (various technical terms used for *tidal rivers* or *estuaries*), and methodology (various technical terms used for *machine learning*). The following search strategy was used for the WoS *TOPIC* section, which searches titles, abstracts, and keywords:

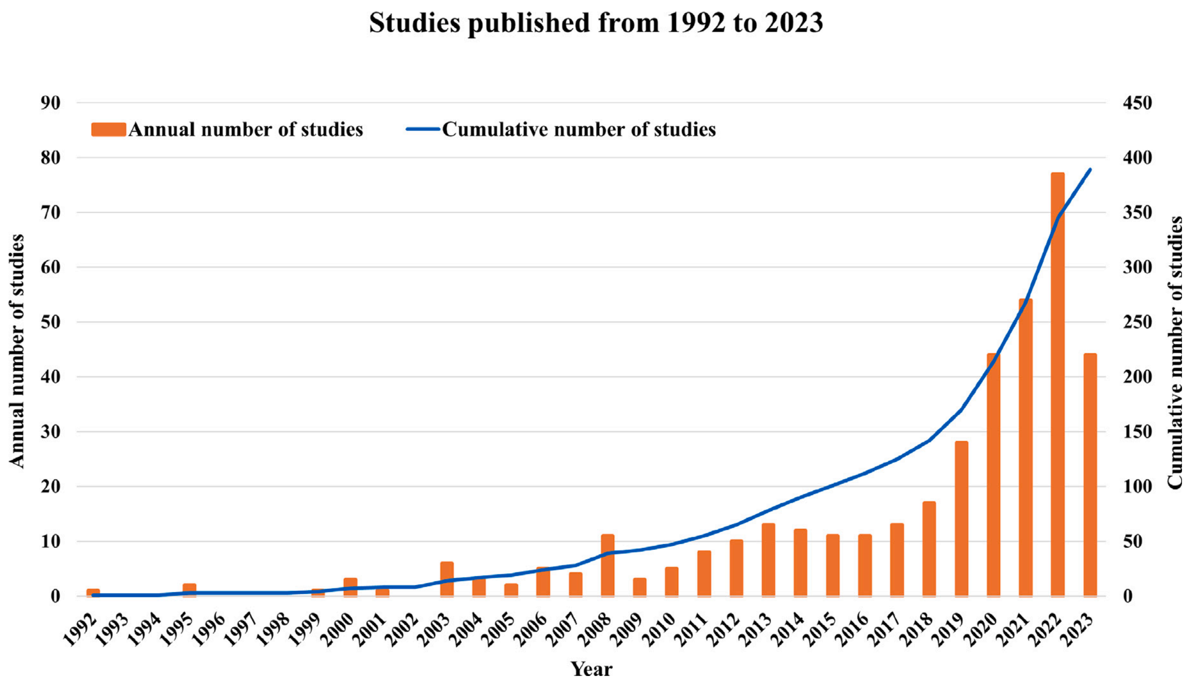

Fig. 2. Annual and cumulative number of ML publications related to water levels and discharge in tidal rivers and estuaries, found in WoS (according to selected keywords) and presented by year of publication (1992–2023).

("level" or "levels" or "stage" or "discharge" or "discharges" or "flow" or "flows" or "streamflow" or "stage-discharge" or "rating curve" or "rating curves") and ("tidal river" or "tidal rivers" or "estuary" or "estuaries" or ("tides" and "river") or ("tides" and "rivers") or ("sea level" and "river") or ("sea levels" and "rivers")) and ("machine learning" or "artificial intelligence" or "neural network" or "neural networks" or "ANN" or "SVR" or "deep learning" or "data driven").

This search resulted in 389 documents (articles and review papers) published in the WoS database. Fig. 2 shows these studies by year of publication, indicating that the subject of this review has become increasingly popular in recent years. More studies were conducted and published in the last five years than in the previous 27 years.

Many of the initial 389 retrieved documents were not directly relevant to modeling, predicting, or forecasting water levels and discharges in tidal rivers and estuaries. A significant portion focused on estimating or forecasting other processes or parameters, like sediment transport, saltwater intrusion, water quality, or biological indicators. Additionally, some studies on water levels or discharges did not consider the crucial interaction between tidal dynamics and river flow. Therefore, only 35 papers (all published within the last 20 years) were selected for further review and detailed analysis after the manual screening of the abstracts.

ML approaches from these studies are classified into the following categories:

(a) statistical models
(b) classifiers, kernel methods, and ensemble
(c) shallow neural network
(d) recurrent neural networks
(e) hybrid models

Furthermore, the studies are grouped and summarized based on the type of analysis:

(a) forecasting studies
(b) reconstruction studies
(c) stage-discharge relationship studies

3.2. Categories of machine learning algorithms

The identification of an appropriate ML approach for estimating the river flow and water level has been the subject of several recent reviews (Yaseen et al., 2015; Mosavi et al., 2018; Sit et al., 2020; Zounemat-Kermani et al., 2020). However, this review focuses on ML approaches developed specifically for tidal rivers and estuaries. Table 1 shows the classification of the 35 selected studies according to ML category. Commonly used ML approaches fall into the following five categories:

1. Simple statistical approach: These methods include Linear Regression (LR), Multiple Linear Regression (MLR), Multiple Polynomial Regression (MPR), Locally Weighted Regression (LWR), AR, Locally Weighted Least Squares (LOESS), Multivariate Adaptive Regression Splines (MARS), and Bayesian Ridge Regression (BRR). In ML studies, they often serve as baseline models for comparison (Wei, 2015; Pasupa and Jungjareantrat, 2016; Thanh et al., 2022) or components within hybrid modeling approaches (Chen et al., 2020).
2. Classifiers, kernel, and ensemble approach: This category includes Decision Tree (DT), Gradient Boosted Decision Tree (GBDT), K-Nearest Neighbors (KNN), Support Vector Regression (SVR), Random Forest (RF), and Light Gradient Boosting Machine (LGBM). These methods generally outperform simple statistical approaches due to their ability to handle nonlinear processes (Wei, 2015; Pasupa and Jungjareantrat, 2016).
3. Shallow neural network (SNN) approach: Feed-Forward Neural Networks (FFNN), Feed-Forward Backpropagation (FFBP), Radial Basis Function Neural Networks (RBFNN), and Multilayer Perceptrons (MLP) are all considered Shallow Neural Networks (SNNs) with one or more hidden layers (Supharatid, 2003b; Tsai et al., 2012; Adib, 2008; Bhar and Bakshi, 2020; Guillou and Chapalain, 2021). Unlike Deep Neural Networks (DNNs), SNNs may struggle with modeling highly complex time series problems. However, they are a popular choice due to their ability to capture nonlinear relationships between input and output data without requiring explicit knowledge of the underlying

Table 1
Reviewed studies on water level and discharge estimation in tidal rivers and estuaries classified by ML category.

Author and year	Simple statistical approach	Classifiers, kernel and ensemble approach	SNN approach	RNN approach	Hybrid approach
Supharatid (2003a)			✓		
Chang and Chen (2003)					✓
Habib and Meselhe (2006)	✓		✓		
Adib (2008)			✓		
Wei and Hsu (2008)			✓		
Chinh et al. (2009)			✓		
Chen et al. (2012)			✓		
Tsai et al. (2012)		✓	✓		✓
Wei (2012)		✓			✓
Yang et al. (2013)					✓
Pierini et al. (2013)			✓		
Liu and Chung (2014)			✓		✓
Gu et al. (2014)					✓
Hidayat et al. (2014)			✓		✓
Wolfs and Willems (2014)	✓		✓		
Wei (2015)	✓	✓	✓		
Pasupa and Jungjareantrat (2016)	✓	✓			
Ahmed et al. (2017)					✓
Garel and D'alimonte (2017)			✓		
Sung et al. (2017)			✓		
Jung et al. (2018)				✓	
Yoo et al. (2020)				✓	
Chen et al. (2020)					✓
Bhar and Bakshi (2020)			✓		
Guo et al. (2021)					✓
Chen et al. (2021)	✓	✓		✓	
Guillou and Chapalain (2021)	✓		✓		
Gan et al. (2021)			✓		
Sampurno et al. (2022)		✓			✓
Thanh Hoan et al. (2022)					✓
Thanh et al. (2022)	✓	✓			
Zhang et al. (2023b)					✓
Fei et al. (2023)					✓
Zhang et al. (2023a)				✓	✓
Vu et al. (2023)				✓	

hydraulic processes (Chen et al., 2012; Hidayat et al., 2014; Guo et al., 2021).

4. Recurrent neural network (RNN) approach: Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) networks are advanced types of RNNs that can effectively model long-term dependencies within data (Yoo et al., 2020). LSTM and GRU are better suited for processing highly complex datasets compared to SNN and simple RNN architectures, which are known to have problems with vanishing gradients and optimization (Vu et al., 2023; Yoo et al., 2020).
5. Hybrid approach: Hybrid models combine ML models with other techniques like signal processing (Discrete/Continuous Wavelet Transform), statistical methods (Least Squares, Cross/Auto-correlation, Partial Auto-correlation), data preprocessing (MA, Exponential Moving Average (EMA)), optimization algorithms (Bayesian optimization (BO), Genetic Algorithms (GA), classifiers (Classification And Regression Trees (CART)), fuzzy logic (Adaptive Neuro-Fuzzy Inference System (ANFIS)), bagging methods, harmonic analysis (NS_TIDE), Artificial Neural Networks (ANNs), and even numerical models (1D, 2D, 3D hydrodynamic models). The primary goal of hybrid modeling is to utilize the strengths of each approach and improve their predictive capabilities (Sung et al., 2017; Fei et al., 2023).

More than half of the reviewed studies rely on SNNs, highlighting their prevalence in this field. However, hybrid techniques are also gaining popularity for water level and discharge estimation in tidal rivers and estuaries.

3.3. Water level and discharge forecasting studies

This section provides an overview of forecasting problems in tidal rivers and estuaries. In general, forecasting studies solve a time series problem by predicting unknown hydrologic parameters in advance using known past values. Most studies in this category focused on forecasting water levels, with the exception of Hidayat et al. (2014) and Vu et al. (2023), which considered discharges. An overview of the reviewed studies is presented in Table 2, which summarizes key details, including authors, year of publication, time scale, input and output parameters, ML method, and evaluation criteria.

3.3.1. Pioneering work (2000–2011)

One of the first applications of a Neural Network (NN) model for forecasting in tidal rivers was presented by Supharatid (2003b). The author constructed a Multilayer Feed-Forward (MLFF) approach using a Levenberg–Marquardt (LM) training algorithm to forecast tidal fluctuations at the Chao Phraya River estuary in Thailand. Two forecasting scenarios were considered: a) day, week, and month, and b) real-time (24 h ahead). Overall, this study showed that the LM training algorithm outperformed the back-propagation (BP) algorithm, more commonly used at the time. The study demonstrated the effectiveness of NNs for long-term water level prediction without requiring explicit computation of tidal harmonic constituents.

In the same year, Chang and Chen (2003) proposed a hybrid model combining a supervised RBFNN with a fuzzy min–max clustering method. This model was applied to forecast water levels of the Tanshui River in Taiwan, considering tides and flood events during typhoons. The input data considered are water level, time, lunar day, and lunar month. The results showed that RBFNNs are efficient tools for forecasting water levels up to one hour in advance during tidal and typhoon effects.

3.3.2. Early applications (2012–2017)

Tsai et al. (2012) introduced a novel approach by combining the decision tree classifier CART with ANN to form a CART-ANN model. This

Table 2
Reviewed forecasting studies in more detail.

Author and year	Time scale	Input	Output	Method	Goodness of fit indices
Supharatid (2003a)	In: hourly, out: hourly, weekly, monthly	Scenario 1: water level	Tidal level	MLFF	EI, RMSE, MAD
	In: hourly, out: hourly	Scenario 2: tidal level	tidal level	MLFF	EI, RMSE, MAD
Chang and Chen (2003)	In: hourly, out: hourly	Lunar month, lunar day, time, water level	Water level	RBFNN	R, RMSE
Tsai et al. (2012)	In: hourly, out: hourly	Precipitation, water level, historic releases	Water level	CART-ANN (MLP, RBF), benchmark models: CART, BPNN, RBFNN	MSE, MAE
Wei (2012)	In: hourly, out: hourly	Water level, average precipitation, reservoir releases	Water level	WSVM, SVM	RMSE
Yang et al. (2013)	In: daily, out: daily	Water level (average value of two time high-tide level)	Water level	CDW-NF, CDW-ANN, CDW-LR	RMSE, MAE, R^2
Hidayat et al. (2014)	In: hourly, out hourly:	Water level, at-site historical discharge data, predicted tide level	Discharge	MLP	RMSE, R^2, NSE
Wei (2015)	In: hourly out: hourly	Water level, average precipitation, reservoir releases, tidal effects	Water stage	LWR, KNN, LR, SVR, ANN	CC, MAE, RMSE, AIC, computational efficiency
Pasupa and Jungjareantrat (2016)	In: hourly, out: hourly	Water level	Water level	LR, KR, SVR, KNN, RF	RMSE
Ahmed et al. (2017)	In: hourly, out: daily	Daily, morning, and night tide data	Tide level	SVR + (MA, EMA)	MAE
Sung et al. (2017)	In: hourly, out: hourly	water level, rainfall	Water level	MLP	RMSE, R^2, NSE
Jung et al. (2018)	In: hourly, out: hourly	Dam discharges, water level, predicted tide level	Water level	LSTM	RMSE, NSE
Yoo et al. (2020)	In: hourly, out: hourly	Precipitation, discharge, tide level	Water surface elevation	LSTM	RMSE, PE, NSE
Chen et al. (2020)	In: hourly, out: hourly	Discharge, tides	Water level	NS_TIDE + AR	RMSE
Guo et al. (2021)	In: hourly, out: hourly	Rainfall, water level, tide	Water level	BO + SVR/RFR, /MLPR /LGBMR	NSE, R^2, MAE, RMSE, PWE, ETP
Chen et al. (2021)	In: hourly, out: hourly	Meteorological data, water level, additional reference factors	Water level	LSTM, BRR, GBDT, LR, SVR	MAE, RMSE, ACC
Zhang et al. (2023b)	In: hourly, out: hourly	Discharge, water level,	Water level	NS_TIDE + (LSTM+FNN+Q, LSTM+FNN, LSTM, AR)	LOSS, RMSE, R^2
Zhang et al. (2023a)	In: hourly, out: hourly	Tide level, meteorological data, time	Tidal level	Cheb-GRU, Conv-LSTM, LSTM, GRU	RMSE, MAE
Vu et al. (2023)	In: daily, out: daily	Piezometer, sea level, air temperature, atmospheric pressure, precipitation, soil moisture, relative humidity, evaporation rate	Discharge	Stacked LSTM	R, R^2, RMSE

hybrid model was used to forecast water levels of the Tanshui River near its mouth, which is affected by tides. CART-RBF outperformed the hybrid model CART-MLP and three reference models (CART, Back-propagation Neural Network (BPNN), RBFNN). However, the authors acknowledged the limitation of the proposed hybrid model, noting its lack of generalization and concluding that the CART-ANN hybrid model is usually case-dependent and limited to the training data domain.

Around the same time, Wei (2012) proposed a new algorithm called Wavelet Kernel Support Vector Machine (WSVM) for forecasting hourly water levels at gauging stations affected by tidal effects during typhoons. The model was again applied to forecasting water levels in the Tanshui River in Taiwan. The input data consists of average precipitation, reservoir releases, and water levels from four gauging stations for 37 typhoon events. Overall, the WSVM model achieved better accuracy compared to the Gaussian Support Vector Machine (SVM).

Yang et al. (2013) developed a hybrid CDW-NN model combining continuous and discrete wavelet transforms (CWT and DWT) with neural networks. The model was used for long-term forecasting of water levels in the Yangtze River estuary. The CWT and DWT were used to determine 15 and 28-day previous data sets as model input. A total of 12 different types of hybrid and pure forecast models were tested and compared. The CWD-Neuro Fuzzy (CWD-NF) model provided the best long-term predictions of water levels as the most efficient multi-step-ahead (MSA) predictor with the lowest error accumulation. One of the main advantages of using neuro-fuzzy systems is the ability to filter the nosily signal in the model input, thus improving the predictive ability.

One of the first attempts to forecast discharges in a tidally influenced river was made by Hidayat et al. (2014). The authors developed an NN forecasting model using MLP that incorporates the LM optimization algorithm due to its fastback progression property, incorporating historical discharge data (Hidayat et al., 2014). The model was applied to forecasting discharges in Samarinda on the Mahakam River. In addition to historical discharge data, water levels (upstream stations, nearby lakes) and predicted tidal levels (outer delta region) were used as inputs. Similar to the study by Yang et al. (2013), wavelet analysis was used to process the tidal data. Analysis of the significance of the inputs showed that the lake's water level had no positive effect on the prediction horizon, indicating the dominance of tidal motion at the observed station. The authors concluded that the proposed NN model performs well for predicting discharges up to two days in advance.

Wei (2015) further investigated water stage forecasting during typhoon events using various machine learning methods categorized as lazy (LWR, KNN) and eager (LR, SVR, ANN), with an unsupervised data splitting method. Inputs to the model were average precipitation, water level (from upstream and downstream stations), reservoir releases, and tidal effect with hourly resolution. The forecast horizon ranged from 1 h to 4 h. Among the eager learning models, ANN and SVR showed better results than LR, and among the lazy learning models, LWR performed better than KNN. However, the comparison of the eager and lazy learning models suggests that no specific group was more effective than the other. Overall, ANN proved to be the most accurate model due to its ability to handle nonlinearities.

A study by Pasupa and Jungjareantrat (2016) compared the harmonic analysis method used for water level forecasting in the Chao Phraya River with various ML models (LR, kernel regression, SVR, KNN, RF). The input data consisted of water levels observed in the last 24, 48, and 72 h, and forecasts were made for the next 24 h. All ML models outperformed the existing method, with SVR using the RBF kernel function providing the most accurate results.

Ahmed et al. (2017) constructed a hybrid SVR model with a sliding window for forecasting tidal levels at various daily scales (1, 2, 5, 7 days) in the Karnaphuli River, Bangladesh. The authors used different types of kernel tricks (neural, radial, and analysis of variance (ANOVA)). In the preprocessing phase, MA and EMA were used, and the data were divided into three parts, creating data subsets consisting of morning, daily, and night tide values. The problem of missing values was solved by using average tide levels. In general, all hybrid ML models achieved high accuracy (over 96%) using the most recent tidal data.

Sung et al. (2017) developed an ANN model to forecast water levels in the Anyangcheon River, a tributary of the Han River in South Korea. The model considered the backwater effect from the main river on tributary water levels. The model considered the backwater effect from the main river on tributary water levels. Statistical analysis indicated reasonable accuracy of the MLP model for forecasts up to two hours in advance, with water levels and rainfall amounts used as input data.

3.3.3. Recent advancements (2018–2023)

Recent advancements in this field have been characterized by hybrid ML models and the introduction of RNN models. Jung et al. (2018) explored a deep learning approach using the LSTM model for water level forecasting in the Han River, South Korea. The model incorporated data on discharges from the dam, water levels, and predicted tide levels. While the model performed well for short lead times (1 h), its accuracy decreased with increasing forecast horizons (up to 24 h).

Building on LSTM, Yoo et al. (2020) proposed an LSTM model with a hybrid activation function to improve flood level prediction in the tidally influenced Hangang River, Korea. The model addressed under-prediction issues and identified tide level, discharge, and precipitation as significant factors through a t-test. The hybrid activation function yielded more precise results than previous single activation functions for up to 6 h of lead time.

Chen et al. (2020) presented a hybrid model combining the nonstationary NS_TIDE model (Matte et al., 2013) and AR analysis to improve short-term water level forecasting in the Yangtze River estuary, China. The model incorporated discharges and tides to achieve more accurate predictions compared to the results obtained by the NS_TIDE model alone.

Guo et al. (2021) investigated the use of data-driven ML approaches for multistep-ahead (MSA) forecasting (up to 6 h) of water level at stations in the tidal reach of the Lan-Yang River, Taiwan. Optimized SVR, random forest (RFR), multilayer perceptron (MLPR), and light gradient boosting machine (LGBMR) models were created using BO. LGBMR emerged as the most accurate model, with observed water levels, tides, and rainfall used as input data.

In addition to the forecasting methods discussed earlier, recent research has explored applications of machine learning for storm surge prediction. For instance, Chen et al. (2021) addressed the challenge of storm surges in estuaries, highlighting the importance of fast and accurate forecasts for disaster mitigation. Their study proposed a novel approach using an LSTM model. The LSTM model incorporated various data sources as input, including meteorological data, water level data, and additional reference factors, to forecast water levels in the Yangtze River estuary. While the model achieved the most accurate results for one-hour lead times compared to traditional models (LR, BRR, SVR, GBDT), its accuracy slightly decreased for longer forecasts (3, 7, and 15 h). However, the error remained within an acceptable range and still outperformed the traditional methods.

Building on the previous work of Chen et al. (2020) and Zhang et al. (2023b) explored a hybrid approach using multiple water levels and a discharge time series as inputs for the NS_TIDE model in the Pearl River Network's tidal West River, China. They combined nonstationary harmonic analysis with a deep learning NN to improve tidal forecasts. Their correlation analysis revealed a direct relationship between errors of the NS_TIDE model and discharge, suggesting that prediction errors increase with sudden discharge changes. Evaluating different combinations of models for short-term error prediction (up to 72 h), they identified that a combination of FFNN on top of the LSTM layer that uses discharge in addition to the previous time series exhibited the best performance, particularly for extreme events, demonstrating significant improvement over the AR approach proposed by Chen et al. (2020).

Zhang et al. (2023a) investigated storm surge prediction using a Chebyshev Graph Convolutional Network (Chebnet) for spatial information extraction and a GRU for capturing temporal dynamics. Their model aimed to forecast storm surges at five tidal stations in the Pearl River Delta, China, with lead times of 1, 3, and 12 h. The model used tidal levels and meteorological data as input. The proposed model outperformed baseline models for past typhoon events, with the advantage becoming more pronounced for longer forecasts.

Vu et al. (2023) investigated a stacked LSTM network for discharge forecasting at five locations in the Loire River System, France. The model incorporated various input parameters, including local and global-scale data (sea level and climate parameters). Due to the diverse data sources and timescales, frequency analysis was employed to optimize lag times and correlations between variables. The model offered accurate forecasts with a lead time of 180 steps (approximately 6 days) for three long-term scenarios (1, 3, and 6 months). While exhibiting good overall accuracy, the model performed better during drought than flood periods.

3.4. Water level and discharge reconstruction studies

In contrast to forecasting, which predicts future hydrologic parameters based on past data, reconstruction studies aim to estimate water levels or discharges at specific locations or for missing intervals within the same time period. These studies typically focus on:

- Estimating hydrologic parameters at a remote or ungauged location (e.g., Gan et al., 2021; Chinh et al., 2009; Sampurno et al., 2022)
- Filling in missing or incomplete data in existing datasets (e.g., Thanh et al., 2022)
- Increasing the temporal resolution (upscaling) of existing data (e.g., Bhar and Bakshi, 2020)
- Modeling historical data — hindcasting (e.g., Thanh Hoan et al., 2022; Hidayat et al., 2014)
- Optimizing the operation of complex water systems (e.g., Wei and Hsu, 2008; Gu et al., 2014)

While traditional hydrodynamic models are often used for these tasks, ML approaches offer a powerful alternative. As in the previous section, the papers with detailed information are summarized in Table 3 for water level and Table 4 for discharge studies.

3.4.1. Pioneering work (2000–2011)

The first studies explored SNN for water level reconstruction in tidal rivers and estuaries. A common approach utilizes ANNs, particularly the MLP architecture. Adib (2008) applied an MLP to estimate water levels in the Karun River, Iran, and Severn River, UK. The model used river discharge, tide elevation, and distance from the river mouth as input, demonstrating its effectiveness as an alternative to hydrodynamic models for various return periods.

Wei and Hsu (2008) developed an optimization model for flood control in a tidally influenced watershed. The model input consisted of estuarine water levels, discharges from reservoirs, total lateral discharges, control point levels, and tributary discharges observed at each hour. The model utilized an FFBP neural network for channel routing, achieving good results in the Tanshui River basin, Taiwan, using observed data from typhoon events. FFBP with the linear channel level routing algorithm proved to be a good alternative to the physically based model.

Just one year later, Chinh et al. (2009) successively applied FFNN to estimate water levels in channels located in a low-lying and flat agricultural basin. Water levels in channels in the Chiyoda Basin, Japan, are affected by a complex interaction between rainfall and downstream water levels influenced by tides. Input variables were selected by considering different hydrological factors, and water levels were estimated at two locations. It was concluded that the proposed FFNN model is useful for estimating water levels in the main channel.

3.4.2. Early applications (2012–2017)

In this period, researchers focused on comparing the performance of ML approaches (primarily ANN) as an alternative to hydrodynamics models, improving hydrodynamic modeling by ML, and shifted from reconstructing water levels to reconstructing discharges.

Chen et al. (2012) compared the efficiency of 2D/3D hydrodynamic models with an ANN for simulating water levels in the Danshui River estuary, Taiwan. While both approaches provided satisfactory results, the ANN outperformed the hydrodynamic models at some gauging stations, likely due to its ability to capture nonlinear relationships. Pierini et al. (2013) compared the performance of an ANN (BPNN) with the MOHID hydrodynamic model for predicting hourly tide levels in the Bahia Blanca Estuary (Argentina). Using only tidal data as input, the BPNN achieved higher accuracy than MOHID, suggesting potential for further improvement by training ANNs with hydrodynamic model outputs.

Furthermore, several studies explored the use of ANNs for improving hydrodynamic modeling, particularly during typhoon events. Liu and Chung (2014) applied BPNN and Genetic Algorithm Neural Network (GANN) models to improve the performance of a 1D hydrodynamic model for simulating water levels in the Danshui River, Taiwan. The 1D hydrodynamic model could not reproduce the water levels at different stations along the river during typhoon events. Both ML models outperformed the hydrodynamic model, with GANN exhibiting higher accuracy during typhoon events.

Machine learning approaches have also been employed for discharge reconstruction in tidally influenced rivers. Gu et al. (2014) developed a framework for optimizing operations in a complex river network using a combination of a River Network Mathematical Model (RNMM), BPNN, and a GA. Each of the methods has a different purpose. RNMM is used to train BPNN, which is then used to define the fitness function for GA, and GA is used to optimize the operating rules for sluice gates. The model was applied to the Pudong New Area of Shangai. The results indicate that the proposed hybrid system is characterized by excellent speed, robustness, and flexibility.

Hidayat et al. (2014) (mentioned previously in the forecasting section) also developed a hindcast model for the tidally influenced Mahakam River, Indonesia. Water levels and tide levels from the outer delta were used as input data but with a small modification related to the inclusion of tidal components obtained by wavelet transform (WT). A hybrid Wavelet Multilayer Perceptron (WMLP) model performed well for hindcasting discharges even without measured data, although minor discrepancies for low and high flows were observed.

Garel and D'alimonte (2017) investigated the use of an MLP to estimate freshwater discharge at the mouth of a narrow estuary (Guadiana estuary, Spain) using data from Acoustic Doppler Current Profilers (ADCPs). Using the principle of maximum entropy, the relationship between mean and maximum velocity was evaluated using data from three cross-channel surveys. The authors also considered using MLP to estimate discharge when the ratio of mean and maximum velocity was unknown. Their findings suggest that MLPs can effectively estimate discharge when trained on data that includes all relevant river dynamics.

3.4.3. Recent advancements (2018–2023)

In the recent period, researchers continued to investigate ML as an alternative to hydrodynamic modeling and to harmonic analysis, they also focused on improving the temporal resolution of data using ML, and developing hybrid ML models. Bhar and Bakshi (2020) established an FFBP using available tide level records from the upstream station to estimate water levels at the downstream station, where data are measured for only half a tidal cycle (12 h) in the Hooghly estuary, India. The FFBP model was used to generate continuous water level data at the remote station, using higher resolution data from the neighboring station as input to the model. The analysis showed that the FFBP model successfully simulated water levels at the downstream

Table 3
Reviewed reconstruction studies of water level in more detail.

Author and year	Time scale	Input	Output	Method	Goodness of fit indices
Adib (2008)	In: daily, out: daily	Discharge, tide elevation, distance from the river mouth	Water level	MLP	R^2
Adib (2008)	In: daily, out: daily	Discharge, tide elevation, distance from the river mouth	Water level	MLP	R^2
Wei and Hsu (2008)	In: hourly, out: hourly	Water level, reservoir discharge, total lateral discharge, control-point levels, tributary discharge	Water level	FFBP, CCCMMOC	RMSE
Chinh et al. (2009)	In: minutes, out: minutes	Water level, rainfall	Water level	FFNN	RMSE
Chen et al. (2012)	In: hourly, out: hourly	Water level, freshwater discharge	Water level	BPNN, vertical 2D, 3D hydrodynamic models	RMSE, R, E
Pierini et al. (2013)	In: hourly, out: hourly	ANN: tidal data, Numerical: water level, current, wind	Tide level	BPNN, MOHID	RMSE, R, SKI
Liu and Chung (2014)	In: hourly, out: hourly	Freshwater discharge downstream water level	Water level	BPNN, GANN	MAE, RMSE, PE
Bhar and Bakshi (2020)	In: half-hourly, out: single day	Tide level	Water level	MLP	RMSE, E, R, MAPE
Guillou and Chapalain (2021)	In: hourly, out: hourly	French tidal coefficient, atmospheric pressure, wind speed river discharge	Water level maxima	MLR, MPR, MLP	MAE, R^2, RMSE
Gan et al. (2021)	In: hourly, out: hourly	River discharge, tide	Water level	LGBM, NS_TIDE	MAE, RMSE, CC, SS
Sampurno et al. (2022)	In: hourly, out: hourly	Discharge, tide, weather parameters	Water level	SLIM 2D + MLR/SVM/RF	RMSE, NSE
Thanh Hoan et al. (2022)	In: daily, out: daily	Water level	Historical water level	Bagging + RF/SMO/M5P, REPT	R^2, RMSE, MAE
Fei et al. (2023)	In: hourly, daily, out: hourly	Discharge, water level, tidal level, precipitation, evapotranspiration	Water level	H2C-XL, HLHC, HHLC, H2C	NSE, KGE

station over neap or spring cycles. This demonstrates the ability of FFBP models to reconstruct missing data with good accuracy, even with limited datasets.

Guillou and Chapalain (2021) compared the performance of multiple regression and MLP models as an alternative to hydrodynamic models for predicting high water levels at high tide in the Elorn estuary, France. Four input variables were considered in terms of tidal effects on water levels: the French tidal coefficients, atmospheric pressure, wind speed, and river discharge. Several conclusions were drawn from this study: (a) MLP performed slightly better than multiple regression, (b) the MLP approaches improved the prediction of maximum water levels compared to extrapolation from downstream data, (c) both ML approaches slightly underestimated the highest water levels, and (d) overall, the use of ML approaches can be recommended for the prediction of high water levels and flooding using short-term weather forecasts.

Gan et al. (2021) investigated the nonlinear and nonstationary interaction of river discharge and tides in estuaries. The authors applied the LGBM model to predict water levels along the lower reaches of the Columbia River, USA. Discharges from two upstream rivers and tides were used as inputs to the model. LGBM was compared to the NS_TIDE model, and results showed comparability in monthly estimation accuracy between the two models, with a phase lag for flood events from the upstream portion of the river. This study emphasizes the importance of considering the interaction between river discharge and tides for water level prediction.

The study by Sampurno et al. (2022) proposed an integrated approach combining a hydrodynamic model (SLIM) and machine learning models (RF, MLR, SVM) to predict compound flooding scenarios in the Kapuas River Delta, Indonesia. The 2D hydrodynamic model SLIM was first used to simulate several compound flooding scenarios, which were then used to train the ML models. The study highlights the effectiveness

Table 4
Reviewed reconstruction studies of discharge in more detail.

Author and year	Time scale	Input	Output	Method	Goodness of fit indices
Gu et al. (2014)	In: hourly out: hourly	Boundary condition, opening degree and time, average stage of inner river, stage of outer river	Discharge, stage	RNMM + BPNN + GGA	RMSE
Hidayat et al. (2014)	In: hourly, out: hourly	Water levels, predicted tide levels, amplitude of tidal components	Discharge	WMLP	RMSE, R^2, NSE
Garel and D'alimonte (2017)	In: daily, out: daily	Velocity	Freshwater discharge	MLP	–
Thanh et al. (2022)	In: daily, out: daily	Water stages	Discharge	GPR, LSSVM, SVR, MARS, DT, RF	RMSE, R, NSE, MAE

of ML for data-scarce regions and identifies the hybrid RF model as most suitable for this application.

Thanh Hoan et al. (2022) developed a hybrid method by combining bagging ensembles with RF, Sequential Minimal Optimization (SMO), and M5P models for estimating historical water levels in the Mekong Delta, Vietnam. All tested models performed well, suggesting the suitability of bagging ensembles for reconstructing historical water level data.

Thanh et al. (2022) investigated the use of various machine learning models (RF, Gaussian Process Regression (GPR), SVR, DT, Least Square Support Vector Machine (LSSVM), and MARS) for reconstructing daily discharge data in the Mekong River Delta. The input data were preprocessed by Fourier series fitting and first-order differences. The study found that ML models outperform traditional rating curves, with RF) and MARS models being particularly well-suited for reconstructing rising limbs of the hydrograph.

Fei et al. (2023) introduced a novel hybrid approach by combining a physical model with ML for water level estimation in the Tianhe-Zhuyin tidal reach of the Xijiang River Basin. Unlike previous studies (e.g. Chen et al., 2020, Sampurno et al., 2022, and Zhang et al., 2023b), this study employed the Hydrologic and Hydrodynamic Coupling Model (H2C). The study used the outputs of the H2C model to further improve water level estimates through a combination of XGBoost and LSTM models. The proposed model H2C-XL achieved superior performance compared to the reference models, particularly during flood events.

3.5. Stage-discharge relationship studies

Defining a relationship between water level and discharge can be considered a special case of the reconstruction problem. The main idea is to estimate the river discharge $Q(x)$ from the observed water level $H(x)$ at the same location. Due to a large number of physical processes (varying river flow, backwater effects, channel cross-section geometry, hysteresis, etc.), modeling the discharge-stage relationship in tidally affected reaches is a highly complex process (Wolfs and Willems, 2014). Outside of tidal influence and under (near) steady-state conditions, a predetermined rating curve (RC) can successfully define this relationship. However, under tidal conditions, the discharge is not only a function of the water level at the same location but also depends on the tidal dynamics (Habib and Meselhe, 2006).

While various ML approaches have investigated the stage-discharge relationship (e.g., Bhattacharya and Solomatine, 2005; Ajmera and Goyal, 2012), only three studies have specifically addressed the problem under tidal conditions. Detailed information about these studies can be found in Table 5. In addition to these studies, we should also mention the studies of Hidayat et al. (2014) and Thanh et al. (2022), which are related to the stage-discharge relationship but focus more on reconstructing discharges under tidal conditions from multiple input data (these studies were described in the previous section, but are included in Table 5).

One of the first attempts to define the stage-discharge relationship using ANN was reported by Supharatid (2003a). The author applied an MLFF neural network that used discharge and tides as input and measured water level as output of the model. The relationship was defined by a two-dimensional RC ($Q-H$ curve for different sea levels). The resulting curves outperformed the standard RC obtained by LR and MLR.

Habib and Meselhe (2006) investigated the construction of an RC in low gradient tidal streams. Due to the multiple RC loops and the complex geometry, the relationship between stage and discharge was modeled using two computational approaches: ANN (namely MLFF) and LOESS. Sensitivity analysis showed that the input variables and measurements from the different stations at the main river and upstream stations were of equal importance. Although both approaches were able to reproduce the nonlinear $Q-H$ relationship, the MLFF demonstrated better generalization and accuracy for extreme discharge values. This study highlighted the necessity of data outside the local water level for accurate discharge prediction.

Wolfs and Willems (2014) compared two RC (Single Rating Curve (SRC), State-Dependent Parameter-Rating Curve (SDP-RC)) with two ML models (MLP ANN and M5 model trees) to determine a stage-discharge relationship in rivers affected by hysteresis. The authors used a hydrodynamic model that was calibrated and validated by field measurements to generate training and validation data and avoid signal noise from measurements. Both rivers experienced backwater effects and unsteady processes. The inputs to the SDP-RC and ML models were local water level and local water level gradient. The results showed that the standard SRC approach produced inferior results compared to the other approaches considered because SRC cannot describe hysteretic behavior. However, the rating curve with SDP-RC was successful in representing complex stage-discharge behavior. ANN outperformed the SDP-RC model for the calibration data but provided less accurate predictions for the validation data, indicating problems with overfitting. The M5 model provided slightly better predictions than the SDP-RC model. The authors recommend SDP-RC due to its interpretability and slight performance advantage over M5 but suggest exploring other ANN models (RBF, ANFIS) for potential improvement.

4. Discussion

The results presented in the previous section provide insights into addressing hydrologic challenges in tidal rivers and estuaries using ML techniques, including forecasting, reconstructing, and establishing stage-discharge relationships. After a careful systematization of the

Table 5
Reviewed stage-discharge establishment studies in more detail.

Author and year	Input	Output	Method	Goodness of fit indices
Supharatid (2003a)	Tidal range, discharge	Water level	MLFF	EI, RMSE, MAD
Habib and Meselhe (2006)	Water level	Discharge	MLFF, LOESS	RMSE, E
Wolfs and Willems (2014)	Local water level, local water level gradient	Discharge	SRC, SDP-RC, MLP, M5	MAPE, RMSPE, R^2, $\bar{R}^2$
Hidayat et al. (2014)	Water levels, predicted tide levels, amplitude of tidal components	Discharge	WMLP	RMSE, R^2, NSE
Thanh et al. (2022)	Water stages	Discharge	GPR, LSSVM, SVR, MARS, DT, RF	RMSE, R, NSE, MAE

studies, we discuss the evolution of ML approaches and provide a critical review by comparing different ML categories and discuss their efficiency when dealing with hydrological processes in tidal rivers and estuaries.

4.1. Evolution of ML approaches for tidal rivers and estuaries

As the results show, the progress and growing popularity of ML approaches for tidal rivers and estuaries has been anything but linear over the years. We address key questions about the presented results, in particular, the frequency of published studies and the growth rate of ML approaches in this area.

4.1.1. Slow gain in the popularity of ML in tidal rivers and estuaries

Although ML methods have been used in river hydrology since 1992, recent advancements have significantly increased its impact and popularity (see Fig. 2). The slow growth in popularity of ML techniques in tidal rivers and estuaries, especially between 1990 and 2000, can be attributed to several factors, including the prevailing popularity of simpler statistical methods, the limitations of early ML models, limited computational power, the unavailability and low quality of observational data, and the multidisciplinary nature of the problem, which requires the collaboration of experts from different fields — hydrology, coastal engineering, and computer science.

A search of the WoS database shows that hydrological studies using simple statistical models are ten times more common than ML approaches. In addition, ML generally requires more computational resources compared to simple statistical methods that were popular in the 1990s and early 2000s (Silberstein, 2006). Data availability was also an important factor during this period. In the 1990s, water level data from gauging stations was often collected manually, and discharges were estimated using RC based on individual field campaigns. Data collection was time-consuming, costly, and inaccurate in highly dynamic river environments.

Furthermore, a high temporal resolution of the data is crucial for capturing the dynamics in coastal environments. A resolution of at least hourly resolution is required for tidal rivers and estuaries. Previous literature reviews on river hydrology by Yaseen et al. (2015) and Zhu et al. (2020) showed that more than 90% of the studies were analyzed on a daily, weekly, monthly, or even annual scale. This difference highlights that most studies analyzed in previous reviews investigated conceptually different processes. It is clear that long-term daily or monthly data are more available compared to hourly data, which is reflected in a smaller number of studies for tidal rivers and estuaries. Furthermore, large data sets are critical to the success of ML approaches, but in the 1990s and early 2000s, large data sets were not readily accessible.

In addition to data limitations, there was a certain degree of skepticism in the scientific community about the interpretability and reliability of "black-box" ML models. Established hydrological models and simpler statistical methods were more favored approaches at the time. All of these reasons, combined with the inherent complexity of tidal river systems, further discouraged early ML research in this area.

4.1.2. Gaps in the frequency of published studies of ML in tidal rivers and estuaries

Despite the widespread use of ML in hydrology today, research on tidal rivers and estuaries is still limited, with clear gaps for longer periods in the past. Noticeable gaps exist in forecasting studies conducted from 2003–2012 and in reconstruction studies prior to 2008, which may seem odd but is consistent with several other reviews of ML studies on water level forecasting.

For example, Zounemat-Kermani et al. (2020) reported only three studies on ML models for surface water level prediction before 2008 and only five studies in the period 2000–2012. Wee et al. (2021) reported the results of 39 studies on water level forecasting, of which only three were published before 2008 and only nine between 2003 and 2012. Zhu et al. (2020) similarly covered 39 studies on ML models for forecasting water levels in lakes and reported on only four studies published before 2008. Note that rivers are generally more common than tidal rivers and estuaries. Furthermore, studies published before 2012 in all three reviews (Zounemat-Kermani et al., 2020; Zhu et al., 2020; Wee et al., 2021) have a monthly or daily time scale, which is unsuitable for tidal rivers and the detection of sub-daily fluctuations. This is inline with Thanh et al. (2022), who showed that most previous studies focused on reconstructing monthly and annual average discharge series. They further argue that studies that have reconstructed daily-averaged discharge series are scarce, likely due to the availability of data and the complex nonstationarity and nonlinearity of daily averaged data. In this context, studies on hourly reconstruction are likely to be even rarer.

These reviews suggest that the simpler ML approaches, data availability and computational power in the 2000s were not suitable to cope with the complex processes in tidal rivers and estuaries, which may explain the gaps in the published studies. The lack of reconstruction studies before 2008 can also be explained by Gill et al. (2007), who argues that a common practice at the time, when preprocessing data for use in hydrological models, was to ignore observations with missing values at a given time step, even if only one of the independent variables was missing. It was only when more advanced ML models became available that hydrologists began reconstructing missing data rather than simply ignoring it.

4.1.3. Limited number of stage-discharges studies in tidal rivers and estuaries

In addition to the research gap mentioned in the previous section, there is also a very limited number of stage-discharge studies. We found only five such studies in tidal rivers. This can be explained by the fact that establishing relationships between water level and discharge in tidal environments is particularly challenging (Bourgault and Matte, 2020). Conventional methods that are suitable for slow, unidirectional flows (e.g. monthly averages in tidal rivers) become unreliable for highly unsteady flows and reverse flows due to tidal currents. The complexity is further increased by the asymmetry of the tides, where the same water level can correspond to opposite discharge values depending on the tidal phase.

In general, there are very few studies that have attempted to solve the problem of determining instantaneous discharges of highly unsteady tidal rivers with flow reversals based on water level alone. Empirical and ML approaches have their limitations. The main drawback of ML methods is that they have limited and questionable predictive capabilities outside their training domain, as they lack the physical fundamentals that drive river flows. In addition, ML methods offer only minimal insight into river mechanics. These are important drawbacks when it comes to understanding the future impacts of climate change on rivers and coastal areas, especially in the context of sea level rise or changes in the hydrological cycle. It is still a widely held opinion that physically based models are preferable to data-driven methods, especially when predictions are to be made outside the training domain, as in climate change research (Bourgault and Matte, 2020). These models take into account the underlying physical processes that drive river flows and thus lead to more robust predictions. The application of ML approaches for the estimation of stage-discharge relationships in tidal rivers and estuaries is still a largely unexplored area of research.

4.1.4. Future opportunities for ML application to tidal rivers and estuaries

Fortunately, recent technological advances are enabling significant growth in the development and application of ML for tidal river research. The limitations that have slowed previous efforts are now being addressed:

- Improved data acquisition: Automated data collection through remote sensing and sensor networks, as well as publicly available large datasets, have greatly improved data accessibility and resolution.
- Improved computing resources: Workstations and supercomputers equipped with powerful graphical processing units (GPUs) and tensor processing units (TPUs), as well as cloud-based platforms (e.g. Google Colab, Microsoft Azure Machine Learning) have significantly accelerated the training process for complex deep learning models.
- Open-source software: Tools such as PyTorch, TensorFlow, and Keras enable researchers to develop, test, and share ML models, fostering collaboration and knowledge exchange.

These advances pave the way for more accurate management of water resources in tidal environments. By improving model predictions for water level and discharge, ML can play a crucial role in mitigating climate change risks such as sea level rise, extreme weather events, and saltwater intrusion.

4.2. Advantages and limitations of ML approaches for tidal rivers and estuaries

After examining previous limitations and research gaps, we conduct a critical review of applied ML approaches and identify their advantages and limitations. Discussing challenges for each model category requires a deep understanding of their architecture and constraints. Before proceeding with modeling, evaluating criteria to select an appropriate ML model is crucial. Factors such as handling nonstationary, nonlinear, and time-varying dynamics of water level and discharge, spatial dependence, computational efficiency, and interoperability are closely related to the model's architecture.

4.2.1. Simple ML approaches

Simple ML approaches (statistical models, classifiers, kernel, and ensemble models) are rarely used in reviewed studies. The first category, representing simple statistical approaches, is identified in 7 out of 35 reviewed studies, while the second category of classifiers, kernel methods, and ensembles is identified in another 7 out of 35 reviewed papers.

Simple statistical models vary in their ability to handle nonlinear and nonstationary data, with some like MPR, BRR, LOESS, and MARS, being more adept at capturing nonlinear or nonstationary relationships compared to simpler linear models like AR and MLR. Simple AR models assume linear relationships between data and, therefore, struggle with nonlinear data. Similar to AR, MLR models assume linear relationships between features and the target variable. For this reason, they are not suitable for nonlinear data. MLR models also assume a constant variance, which may not hold for nonstationary data. MPR models extend MLR by adding polynomial terms to the features. They can partially capture nonlinear relationships but suffer from overfitting if too many high-degree terms are included. BRR models were developed primarily for regularizing MLR to avoid overfitting, they can handle some nonlinearity by implicitly creating smoother decision boundaries. However, they are not designed specifically for nonlinearity. LOESS models are non-parametric methods that fit a small linear regression model to local subsets of the data. They can adapt to nonlinear patterns but may not capture complex nonlinear relationships. Similar to LOESS, LWR models fit a linear model locally but assigns weights to data points based on their distance from a query point. They can capture local nonlinearity but may not generalize well to unseen data. MARS models build a piecewise linear model by recursively splitting the data space and fitting linear models in each region. They are more flexible for nonlinear and nonstationary data but can be complex to interpret and prone to overfitting.

The second category of simple ML approaches can model nonlinear processes but struggles with nonstationary data. In contrast to classifiers and ensemble models, kernel methods (KNN and SVR) cannot directly handle missing data. Classifiers offer higher interpretability than ensemble models and kernel methods due to their simple architecture. Even though this category of ML models cannot directly capture spatial variability, they can still incorporate temporal dependency using lagged variables containing historical records.

However, even simple ML models like LR, kernel regression, SVR, KNN, and RF can outperform harmonic analysis for tidal prediction (Pasupa and Jungjareantrat, 2016). Similar models such as RF, GPR, SVR, DT, LSSVM, and MARS were found to outperform the RCs in estimating stage-discharge relationship (Thanh et al., 2022). Harmonic analysis and RC share the same sensitivity to outliers and noise, and may require constant recalibrations. Although recalibration is typically not required for ML models, retraining them periodically is recommended when dealing with tidal data.

4.2.2. Shallow Neural Network (SNNs)

The prevalence of SNNs in predicting water levels and discharges in tidal rivers and estuaries is evident in 17 out of 35 reviewed research papers. Classic ANNs, such as FFNNs with the BP algorithm or MLPs with a single hidden layer, were the common choices (Supharatid, 2003b; Habib and Meselhe, 2006; Wei and Hsu, 2008). Only a few studies deviated from this simple architecture (Adib, 2008; Guillou and Chapalain, 2021). SNNs introduce nonlinearity into the model architecture via activation functions like Rectified Linear Unit (ReLU), with algorithms like LM which can improve training speed and efficiency compared to BP. Reviewed studies have shown that compared to BP, these ML algorithms offer faster convergence and are more resilient to noise in the data. Similar to kernel methods and statistical methods, ANNs require preprocessing for missing data. They also utilize lagged inputs to capture temporal dependencies.

Several studies have compared SNNs with hydrodynamic models when simulating physical processes in tidal rivers and estuaries. SNNs generally outperform hydrodynamics models in accuracy and ability to preserve nonlinear characteristics between input and output variables (Chen et al., 2012; Pierini et al., 2013; Liu and Chung, 2014). The adaptable nature of SNNs enables better generalization of complex tidal river dynamics compared to hydrodynamic models, especially during peak water levels and during typhoon events.

Nevertheless, there are some notable limitations of SNN models, such as:

(a) the reliability and accuracy of models may be affected by the size of the data set (e.g., Pierini et al., 2013; Hidayat et al., 2014)
(b) they are sensitive to spatial variability, model performance decreases if input datasets are physically located further away from the location (e.g., Bhar and Bakshi, 2020),
(c) the full dynamics of the river and water level (entire range of values) must be captured in a training set of data to provide accurate estimates (e.g., Garel and D'alimonte, 2017), and
(d) as lead time increases in forecasting studies, results become inconsistent, and under- and over-prediction become more common (e.g., Supharatid, 2003a; Hidayat et al., 2014; Yoo et al., 2020).

4.2.3. Recurrent Neural Networks (RNNs)

The application of advanced RNNs, particularly LSTM networks, has been gaining popularity in recent years (5 out of 35 studies in a recent survey). The application of advanced RNNs in hydrological modeling experienced a significant increase in 2023, which aligns with a broader trend in hydrology emphasizing the importance of capturing long-term dependencies. They possess several key features that make them well-suited for tidal rivers and estuaries. LSTMs utilize gating mechanisms to selectively remember or forget past information. This allows them to learn and retain relevant long-term dependencies within the data sequence. Unlike traditional ANNs, LSTMs have internal memory cells that can store past information critical for predicting future water levels. This memory capability is crucial for capturing the influence of historical events on current river conditions. Additionally, the Backpropagation Through Time (BPTT) algorithm efficiently trains RNNs by backpropagating errors through the entire sequence, allowing the model to learn from past errors and improve its predictions for future time steps.

Advanced RNNs offer a significant advantage over simpler models like ANNs and SVMs when dealing with long-term dependencies in hydrological data. Traditional ANNs can suffer from vanishing gradients in long sequences. This makes it difficult for the model to learn from distant historical data points, hindering its ability to capture long-term trends. While SVMs are powerful tools, they often struggle with nonstationary data, which is common in hydrology due to factors like seasonal variations. Also, they can adapt better to these evolving patterns in the data.

Advanced RNNs are particularly well-suited for modeling tidal river water levels. These environments exhibit complex relationships between various factors, including tidal dynamics, river discharge, and meteorological factors (rainfall and wind can also impact water levels by altering river discharge and influencing storm surges). They can effectively capture these nonstationary relationships by learning from historical data. Their ability to model long-term dependencies makes them a well-suited approach for predicting the dynamics of tidal river water levels. While they offer significant advantages, a potential limitation is their computational complexity. The training process, especially for LSTMs, requires more computational resources compared to simpler models. Additionally, their complex internal structures can make them less interpretable compared to simpler models.

4.2.4. Hybrid approaches

Hybrid approaches combining different techniques are the second most common category in this review (occurring in 15 of 35 studies). The first such application in tidal rivers dates back to 2003 (integration of RBFNN with fuzzy logic). Hybrid models have emerged as a promising research direction in this field and often outperform pure ML approaches (as shown by the studies of Yang et al., 2013; Ahmed et al., 2017; Chen et al., 2020; Sampurno et al., 2022). The combination of ANNs with hydrodynamic models, for example, utilizes the strengths of both — the ability of ANNs to capture complex relationships and the process knowledge of hydrodynamic models.

Several studies (Wei, 2012; Yang et al., 2013; Hidayat et al., 2014) have successfully integrated different ML models (SSVM, LR, MLP) with Wavelet Transform (WT). The strength of WT lies in its ability to perform multi-scale analyses. Thus, hydrological time series data can be decomposed into different frequency components to capture variations on different temporal scales (e.g. daily, seasonal, tidal). By incorporating WT features alongside observed data, hybrid models can extend prediction horizons beyond the limitations of individual models. This enables earlier warnings and better preparation for potential flood events. Multi-scale analysis of WT helps to isolate noise and nonstationary components in the data. This can lead to more accurate modeling predictions by focusing on the information relevant to water level forecasting. By capturing the rapid changes associated with extreme events such as typhoons, WT-ML models can improve forecast accuracy. However, these benefits come at the expense of computational resources and the time required to determine the optimal WT parameters. Decomposing and analyzing data by WT can be computationally intensive, especially for long time series or high-resolution data. Finding the optimal WT parameters for a given data set requires additional computational resources and expertise.

The combination of simple ML algorithms with nonstationary harmonic analyses, such as the NS_TIDE model and the AR analysis (Guo et al., 2021), increased the accuracy in short-term forecast of water levels in estuaries. Although the inclusion of AR analysis was better than NS_TIDE alone, the increasing error accumulation when the forecast horizon is extended is a major problem. Combining the NS_TIDE model with LSTM, FFNN and discharge time series can further improve the accuracy (Zhang et al., 2023b). Another hybrid approach emphasized the importance of incorporating discharge time series into water level prediction and integrated hydrologic, hydrodynamic, XGBoost, and LSTM models (Fei et al., 2023). The inclusion of XGBoost in the hybrid model helps to capture complex relationships, process missing data, and gain insights into the importance of features.

Other types of hybrid models also show potential in this area of research. The combination of supervised and unsupervised learning techniques, e.g. the RBFNN model of Chang and Chen (2003), can achieve faster training speeds, reliable hourly forecasts, and peak flow capture compared to stand-alone ANNs. Hybrid models such as CART-ANN and CART-RBF (Tsai et al., 2012) show improved prediction capabilities for typhoon events. Ensemble models combined with ANNs generally improve generalization with unseen data. However, this generalization is limited if various ranges of data are not equally represented. Studies by Ahmed et al. (2017) and Guo et al. (2021) show successful applications of hybrid models that include SVR, ensemble models, and optimization techniques for water level prediction. However, these models may have problems with global optimization for high-dimensional data. The bagging-based hybrid model provided similar prediction results with high accuracy (Thanh Hoan et al., 2022). Although hybrid models offer numerous advantages, they come with some limitations. The computational effort and time required to find the optimal parameters can be considerable (e.g. for WT-based approaches). In addition, combining ensemble models with ANNs can lead to biases if the training data is not diverse enough to represent the different data ranges.

Hybrid approaches have also demonstrated the ability to capture both spatial and temporal features. A combination of two RNN models (LSTM and GRU) with Convolutional Neural Network (CNN) overcame the previous limitations of the individual models. Although this type of hybrid approach was already known in the field of hydrology, it has only recently been applied to coastal rivers (Zhang et al., 2023a). Increased model complexity can lead to longer training times but can significantly improve the results.

5. Conclusion

The review focused on studies that investigated estuaries, tidal rivers, and some of their tributaries with the aim of forecasting and reconstructing water levels and discharges using various ML methods, signal processing, statistical methods, and optimization algorithms. The physical processes in tidal rivers and estuaries are influenced by nonlinear interactions between river flows and tidal dynamics, which makes estimating water levels and discharges challenging, especially under extreme weather conditions. An evaluation of the different models is important to better understand the advantages and limitations of each model for a specific application. In contrast to previous reviews that focused on inland water systems, the novelty of this review lies in the shift of focus to coastal environments, namely tidal rivers and estuaries, which are more complex, subject to different hydrological, coastal and meteorological influences, characterized by a high degree of nonlinearity and nonstationarity, and therefore require a much higher temporal resolution. This, in turn, has implications for the selection and performance of ML approaches.

In summary, most studies applied ML for forecasting water levels in tidal rivers and estuaries, some studies investigated the reconstruction of water levels using neighboring stations or other hydrological and meteorological parameters, whereas only a few studies attempted to estimate river discharges using other hydrological parameters. Only five studies proposed solutions to a stage-discharge relationship in a tidal river. Such a state of research suggests that estimating discharges in tidal-affected regions is still a complex task that needs further research.

Most studies used standard ANN, but recently more authors are developing hybrid approaches. The results suggest that data preprocessing techniques can improve the overall performance of the models. It is critical to carefully select and filter the valuable information that is passed to the model ML. The most common hybrid choice for tidal rivers and estuaries was a combination of ML, Wavelet transforms, and nonstationary harmonic analysis. Various optimization algorithms such as LM, GA, GGA, and BO are beneficial for avoiding overfitting problems. The hybrid model approach was of outstanding importance as it could solve simple problems that single ML models could not.

In recent years, new ML approaches have been developed and applied to solve various problems in hydrology. However, there are several approaches that have not been applied specifically to tidal rivers and estuaries but have the potential to improve the prediction of water levels and discharges: Emotional Neural Network (ENN) (Yaseen et al., 2020), Counter-propagation Fuzzy Neural Network (CFNN) (Chang and Chen, 2001), Wavelet-Bootstrap ANN (WBANN) (Tiwari and Chatterjee, 2011), CNN (Song, 2022), Fourier transform (FT) combined with CNN (Khan et al., 2021), Physics Informed Neural Networks (PINN) (Lu et al., 2021), and Large Language Models (LLMs) adapted to time series (Jin et al., 2023). For this reason, some suggestions are given for future research:

- In general, the data inputs for ANN and DNN methods are one-dimensional (1D) time series. Therefore, it is challenging for these methods to process 2D series or spatial data that may be relevant to hydrologic processes. On the other hand, CNNs are typically used for image classification and, therefore, can use spatial features to improve predictive capabilities. The further improvement of the approach combining CNNs and LSTMs (Baek et al., 2020) seems to be a promising direction for future research.
- FT is a signal processing method similar to WT. It differs from WT because it transforms the signal into a frequency domain, identifying the frequencies present and their components. In previous studies, the short-time Fourier transform (STFT) has been used for network attack detection (Khan et al., 2021), electrocardiogram signal classification (Huang et al., 2019), and emotion detection (Satt et al., 2017), feeding the Deep Neural Network (DNN) with spectrograms as input data. Each of these applications represented an improvement over the previously used methods. Therefore, FT as a hybrid approach (such as FT-CNN, FT-LSTM, FT-SVR, and FT-MLP) is a potential method for future research on estimating water level and discharge of tidal rivers and estuaries. Other hybrid ML subtypes not previously considered include WT-LSTM, CNN-LSTM, and WT-ANFIS.
- The attention mechanism is a technique used to improve neural network performance, is commonly used with sequential data, and can effectively handle large datasets. It works on the principle of adding different weights to the parts of the input sequence based on their relevance for solving specific problems. They are commonly applied as part of sequence models, Encoder-Decoder, or Transformer architectures, and what differentiates them from other mechanisms is their ability to provide interoperability to some extent (Niu et al., 2021). Based on WOS, this mechanism has only been recently applied (since 2023, 10 papers available) in the field of hydrology. Hence, its utilization should be further investigated for tidal rivers and estuaries.
- Unlike physics-based models, all ANNs discussed in this review do not consider the principle of conservation of mass and momentum, which are critical for describing hydraulic processes in tidal rivers and estuaries. ANNs "learn" the laws of physics during their training phase based solely on observations, so ANNs require large amounts of data because their performance depends on it. Few of the studies were conducted in data-poor regions. Therefore, it is of great interest to assess how different hybrid methods would perform in the presence of limited data and to suggest how this problem can be resolved.
- One solution for data-poor regions is PINN — a machine learning technique used to solve problems involving PDEs, such as Shallow Water Equations (SWE) describing flow in tidal rivers and estuaries. The PINN approach is a mesh-free technique that approximates PDE solutions by converting the problem of directly solving the governing equations into a loss function optimization problem. In this way, PINNs take into account the physics of the problem (described by PDEs) rather than trying to guess the solution based solely on observational data (Jamali et al., 2021). In addition to PINNs, one of the possible development directions for data-scarce regions could be to combine ANNs with physics-based models. This hybrid approach would involve calibrating a hydraulic model with measured data and then using that model to generate a much larger dataset containing a wide range of (extreme) conditions that can be used to train ANNs.
- Finally, Large Language Models (LLMs) hold immense promise for advancing time series forecasting in tidal rivers and estuaries. Unlike specialized models that cater to specific tasks, LLMs offer a more general, efficient, synergistic, and accessible approach. Their robust pattern recognition and reasoning abilities over complex sequences of tokens have been well-documented in natural language processing (NLP) and computer vision. However, adapting these powerful models to time series data has been challenging due to data sparsity. In response, the Time-LLM framework was recently introduced (Jin et al., 2023). It reprograms LLMs for time series forecasting while keeping their language models intact. By aligning time series data with text prototypes and leveraging techniques like Prompt-as-Prefix, Time-LLM outperforms specialized forecasting models. This innovative fusion of language models and time series data holds the potential to significant improvement of capabilities for predicting hydrological parameters in tidal rivers and estuaries.

Given the rapid progress and advancement of machine learning, future studies should not only evaluate how different methods of ML perform under specific conditions and constraints. It is necessary to propose holistic solutions for water management that include the optimal number, location, and type of monitoring stations, and also combine physically-based models with signal processing and ML algorithms.

6. Abbreviations:

ACC	accuracy level
AC	auto-correlation
ADCP	Acoustic Doppler Current Profiler
AIC	Akaike's Information Criterion
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
AR	Auto Regressive
ARIMA	Auto Regressive Integrated Moving Average
ARMA	Auto Regressive Moving Average
BO	Bayesian optimization
BP	Back-propagation
BPNN	Back-propagation Neural Network
BPTT	Back-propagation Through Time
BRR	Bayesian Ridge Regression
CART	Classification And Regression Tree
CC	cross-correlation
CDW	Continuous and Discrete Wavelet Transformation
CFNN	Counter-propagation Fuzzy Neural Network
Chebnet	Chebyshev Graph Convolutional Network
CNN	Convolution Neural Network
CWT	Continuous Wavelet Transform
DL	Deep Learning
DNN	Deep Neural Network
DT	Decision Tree
DWT	Discrete Wavelet Transform
EI	efficiency index
EMA	Exponential Moving Average
ENN	Emotional Neural Network
ETP	error of time-to-peak
FFBP	Feed-Forward Back Propagation
FFNN	Feed-Forward Neural Network
FT	Fourier Transform
GA	Genetic algorithm
GANN	Genetic Algorithm Neural Network
GBDT	Gradient Boosted Decision Tree
GGA	Generalized Genetic Algorithm
GPR	Gaussian Process Regression
GPU	graphical processing unit
GRU	Gated Recurrent Unit
H-ADCP	Horizontal Acoustic Doppler Current Profiler
H2C	Hydrologic and Hydrodynamic Coupling model
H2C-XL	Hydrologic and Hydrodynamic Coupling model - XGBoost and LSTM
HHLC	Hydrologic-Hydrodynamic-LSTM Coupling model
HLHC	Hydrologic-LSTM-Hydrodynamic Coupling model
KNN	K-Nearest Neighbor
LGBM	Light Gradient Boosting Machine
LGBMR	Light Gradient Boosting Machine Regression
LLM	Large Language Models
LM	Levenberg–Marquardt
LOESS	Locally Weighted Least Squares
LR	Linear Regression
LS	Least Square
LSSVM	Least Squares Support Vector Machine
LSTM	Long short-term memory
LWR	Locally Weighted Regression
MA	Moving Average
MAD	mean absolute deviation
MAE	mean absolute error
MAPE	mean absolute percentage error
MARS	Multivariate Adaptive Regression Splines
MI	Mutual information
ML	Machine Learning
MLFF	Multilayer Feed-Forward
MLP	Multilayer Perceptron
MLPR	Multilayer Perceptron Regression
MLR	Multiple Linear Regression
MPR	Multiple Polynomial Regression
MSA	multi-step-ahead, multistep-ahead
MSE	mean squared error
NF	Neuro Fuzzy
NLP	Natural Language Processing
NN	Neural Network
NS_TIDE	nonstationary Tidal Harmonic Analysis
NSE, E	Nash–Sutcliffe efficiency coefficient
PAC	Partial auto-correlation
PDE	partial differential equations
PE	peak error
PINN	Physics Informed Neural Network
PWE	peak water-level error
R, CC	correlation coefficient
R^2	coefficient of determination
$\bar{R}^2$	adjusted R^2
RBF	Radial Basis Function
RBFNN	Radial Basis Function Neural Network
RC	Rating Curve
ReLu	Rectified Linear Unit
REPT	Reduced Error Pruning Trees
RF	Random Forest
RFR	Random Forest Regression
RMSE	root mean square error
RMSPE	root mean square percentage error
RNN	Recurrent Neural Network
RNMM	River Network Mathematical Model
SAR	Spatial Autoregressive Model
SDP-RC	State Dependent Parameter-Rating Curve
SKI	skill index
SMO	Sequential Minimal Optimization
SNN	Shallow Neural Network
SRC	Single Rating Curve
SS	skill score
STFT	Short-time Fourier transform
SVM	Support Vector Machine
SVR	Support Vector Regression
SWE	Shallow Water Equations
TPU	tensor processing unit
WBANN	Wavelet-Bootstrap ANN
WMLP	Wavelet Multilayer Perceptron
WoS	Web of Science
WSVM	Wavelet Kernel Support Kernel Machine
WT	Wavelet Transform
XGBoost	eXtreme Gradient Boosting

CRediT authorship contribution statement

Anna Maria Mihel: Conceptualization, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Jonatan Lerga:** Conceptualization, Formal analysis, Funding acquisition, Project administration, Resources, Supervision, Validation, Writing – review & editing. **Nino Krvavica:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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