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Hydrodynamic Flow Models and Machine Learning for Cross-Current Prediction (IJmuiden Case Study)

Introduction

Safe navigation in coastal waters often depends on accurate predictions of currents, especially **cross-currents** that push vessels laterally. At the IJmuiden harbor (the seaward entrance to the North Sea Canal leading to Amsterdam), strong tidal currents and eddies around the breakwaters create challenging cross-currents for ships. For example, peak tidal flows at IJmuiden can reach ~0.7 m/s (about 1.4 knots) during flood tide, generating large eddies at the harbor entrance [1]. In fact, harbor pilots impose limits on cross-current for deep-draft ships: in IJmuiden, ships over 14.1 m draft face a **1-knot cross-current restriction** [2]. This means port authorities and Rijkswaterstaat (RWS) must carefully time ship entries around slack tides when lateral currents subside. To support such decisions, **physics-based hydrodynamic models** and increasingly **machine learning (ML)** techniques are used to forecast currents. This report reviews commonly used 1D/2D/3D flow models for estuarine and coastal current prediction (with emphasis on IJmuiden and Dutch examples), how RWS applies these models for cross-current forecasting, and how ML is enhancing or hybridizing with these models. We also present case studies of ML–model integration, compare physical vs. data-driven vs. hybrid approaches, and discuss how ML-enhanced models can be implemented in operational forecasting systems like Delft-FEWS.

Conventional Hydrodynamic Flow Models (1D, 2D, 3D)

Hydrodynamic flow models solve physical equations (primarily the Navier-Stokes equations or simplified shallow-water equations) to simulate water movement. These models come in various dimensional configurations: **1D models** simulate flow along a single dimension (e.g. along a river or channel), **2D models** simulate depth-averaged horizontal flows (good for wide shallow areas), and **3D models** resolve vertical layers to capture stratification and vertical circulations. In coastal and estuarine contexts, 2D and 3D models are most relevant: 2D models assume the water column is well-mixed vertically, whereas 3D models account for density differences (salinity, temperature) and vertical current profiles. Below we outline some widely used flow modeling systems, with a focus on those prevalent in the Netherlands and Europe:

- **WAQUA / TRIWAQ (SIMONA)** – A Dutch hydrodynamic modeling system developed for RWS. WAQUA is the 2D shallow-water flow model and TRIWAQ is the 3D version; together they simulate water levels, currents and water quality in well-mixed estuaries, coastal seas, and rivers [3]. These models solve the shallow-water equations on a rectilinear or curvilinear grid. WAQUA (depth-averaged) is computationally faster, while TRIWAQ includes vertical density stratification and thus more accurately captures 3D circulation (at the cost of longer run times) [4]. WAQUA/TRIWAQ can simulate tides, wind-driven flows, and even transport of temperature, salinity, or tracers [5]. Commissioned by Rijkswaterstaat, WAQUA/TRIWAQ models have been built for much of the Dutch coast, estuaries, and rivers [6]. For example, a WAQUA/TRIWAQ-based operational model runs for the Port of Rotterdam, providing 24-hour forecasts of water levels and currents to support port operations [6].

This system has been a workhorse for Dutch water management, including scenarios like IJmuiden where 3D effects (fresh lock water meeting salty sea) can be important.

- **Delft3D** – A widely used suite of hydrodynamic and morphodynamic models developed by Deltares (NL). Delft3D-Flow is a 2D/3D finite-difference model solving fluid flow on a structured grid; it's often coupled with wave (SWAN), sediment, and water quality modules. Delft3D has been applied globally for coastal, estuary, river, and harbor studies. Along the Dutch coast, it has been used to model tidal currents, storm surges, and morphological changes. For instance, Delft3D was used to analyze the hydrodynamics around IJmuiden's extended harbor moles and their impact on sedimentation patterns [7]. Typical use-cases range from short-term simulations of a few tidal cycles to long-term morphology runs over decades, covering spatial scales from a few kilometers (for detailed harbor studies) up to tens of kilometers for regional coastal modeling [8]. Originally Delft3D used rectangular grids, but modern versions (the **Delft3D Flexible Mesh** or D-HYDRO suite) allow unstructured grids. In fact, Rijkswaterstaat's next-generation models are built in the Delft3D FM framework – for example, the new Dutch Continental Shelf Model uses Delft3D FM with resolutions down to 100 m on the coast [9] (more on this in the RWS section). Delft3D's 3D mode allows simulation of stratified estuaries, making it suitable for areas like the Rotterdam Waterway or IJmuiden locks where freshwater outflow overlies seawater.

- **Telemac-Mascaret** – An open-source European modeling suite (initially developed by EDF, France) that includes TELEMAC-2D (depth-averaged) and TELEMAC-3D hydrodynamic models, among other modules (SEDIMENT for morphology, TOMAWAC for waves, etc.). TELEMAC uses unstructured finite-element or finite-volume grids, giving flexibility to resolve complex coastlines and bathymetry with variable resolution. It's used by many agencies and researchers across Europe for coastal and estuary studies. For example, the Flemish Waterway Authority (Waterbouwkundig Laboratorium) built an "Scaldis-Coast" model using TELEMAC-2D for hydrodynamics coupled with TOMAWAC for waves to simulate the Belgian coast and Western Scheldt estuary [10] [11]. This model employed grid resolutions from 750 m offshore down to 25 m nearshore around complex geometry like breakwaters [11]. TELEMAC's strengths include parallel scalability and the ability to cover large domains with local refinements, which is useful in tidal estuaries. While TELEMAC might not be as commonly used by Rijkswaterstaat (who historically use WAQUA/Delft3D), it is a **standard tool in European coastal engineering**, and Dutch consultants or researchers occasionally use it in projects (especially in collaboration with Belgian or French partners). TELEMAC-3D can handle stratification and has been applied to estuarine flows and even the Scheldt's salt intrusion problems in research contexts [12] [13].

Other Examples: There are numerous other flow models; for completeness, notable mentions include **MIKE 21/3** (2D/3D models by DHI, used internationally for coastal projects), **ROMS** (a 3D ocean model often used in research), and **1D network models** like SOBEK or HEC-RAS for rivers and channels. In Dutch practice, 1D models are used for rivers and canal networks (e.g. SOBEK for river flow forecasting), but for predicting cross-currents in open harbors like IJmuiden, 2D/3D models are essential. Table 1 summarizes key features of the main modeling systems:

Model	Dimensionality	Grid Type	Typical Application Domain	Example (NL/Europe)
WAQUA/ TRIWAQ (SIMONA)	2D or 3D (barotropic/ baroclinic)	Rectangular or curvilinear (structured)	Tidal rivers, estuaries, North Sea coast (operational forecasts)	Dutch North Sea and estuaries (RWS); Port of Rotterdam 3D forecast model [6].
Delft3D (classic & FM)	2D or 3D (hydrostatic)	Rectangular (classic) or unstructured flexible mesh (FM)	Coastal areas, estuaries, coastal morphology studies, climate scenarios	Holland Coast tidal modeling around IJmuiden (morphological impact of harbor moles) [7]; national storm surge models (DCSM).
Telemac (Telemac-2D/ 3D)	2D or 3D (hydrostatic)	Unstructured (finite-element/ vol.)	Coastal zones, estuaries, river-coastal coupling, often where flexible meshing needed	Integral model of Belgian coast & Scheldt (Scaldis-Coast) with TELEMAC-TOMAWAC [10] [11]; various European harbor studies.
Others (MIKE, etc)	1D, 2D, or 3D (varies)	Structured or Unstructured	Rivers, floodplains, coastal (depending on model)	MIKE 21 for coastal engineering (used by consultants worldwide); SOBEK 1D for Dutch river networks.

The choice of model depends on the **scale and physics required**. For predicting currents in a well-mixed tidal channel or open coast (like the IJmuiden approach channel), a depth-averaged 2D model may suffice. However, in cases with significant vertical salinity stratification or vertical shear (e.g. outflow from the North Sea Canal locks at IJmuiden creating a freshwater plume over saltwater), a 3D model (TRIWAQ, Delft3D-3D, or TELEMAC-3D) is needed for fidelity [4]. All these models require input data like bathymetry, open-boundary tidal water levels, wind forcing, etc., and must be calibrated/validated against measurements (current meter data, tide gauges) to ensure accuracy.

Use of Flow Models by Rijkswaterstaat for Cross-Current Prediction

Rijkswaterstaat (RWS) – the Dutch water management agency – has a long history of using hydrodynamic models for forecasting water levels and currents. RWS operates the national forecasting systems for North Sea tides and storm surges, as well as regional models for coastal waters and navigation channels. Historically, RWS's primary tools were WAQUA (2D) and TRIWAQ (3D) models running in the **SIMONA** framework, which provided operational water level and current forecasts at key locations. For instance, RWS's Hydro Meteo Centrum (HMC) uses these models to issue daily tide and current predictions for ports and pilot organizations. In the IJmuiden region (IJmond), RWS provides a *"Dwarsstroom"* (cross-current) forecast to the Pilots and Port Authority – essentially a prediction of the lateral current in the IJmuiden outer channel, based on model simulations combined with astronomical tide calculations [14] [15]. This allows harbor planners to know when the cross-current will drop below the 1-knot safety threshold for deep ships [2]. Such forecasts are crucial because, as one pilot described, at IJmuiden the peak tidal stream occurs ~30 minutes before high water, and certain large vessels must delay entry until the ebb current slackens sufficiently [2]. RWS's models help identify these safe windows, balancing current strength against available water depth (which starts reducing after high tide).

RWS typically employs **2D shallow-water models for tide and surge forecasts** covering the North Sea and adjacent waters. The Dutch Continental Shelf Model (DCSM) is a prime example – it's a large-scale model of the NW European shelf that has been refined over generations. The latest version, **DCSM-FM (Flexible Mesh)**, is a sixth-generation model developed by Deltares for RWS [16]. It is the successor to the old WAQUA-based DCSM (v5/v6) and uses the modern Delft3D-FM code on an unstructured grid [17] [18]. The DCSM-FM actually comes in two flavors: a coarse 0.5′ grid (~900 m) 2D model for ensemble and long-range forecasting, and a fine ~100 m grid model with refined coastal resolution for detailed deterministic forecasts [9]. The fine model includes most Dutch coastal waters (Wadden Sea, Zeeland estuaries) with high detail, and is aimed at providing accurate water level and current forecasts to HMC and the Water Management Centre Netherlands (WMCN) [19]. In operational practice, RWS uses these models to drive forecast bulletins and web portals (e.g. waterberichtgeving.rws.nl) that disseminate **predicted tidal currents**. For example, RWS's online system shows vector currents in the IJmuiden outer fairway based on the model, alongside measured data from a current meter pile [14] [15]. This information is used by the **Dutch Pilots Association (Loodswezen)** and the Port of Amsterdam for navigation planning.

Another concrete use-case is **Rotterdam's Port Approach**: as mentioned earlier, a WAQUA/TRIWAQ model is run operationally for the Port of Rotterdam (Eurogeul/Maasgeul channels and harbor) to give 24h forecasts of currents, water levels, and even salinity [6]. This system, developed by Svašek on behalf of RWS, aids in guiding large ships through the Nieuwe Waterweg and preventing grounding or collision due to unexpected currents. We can infer a similar setup can be (or has been) applied to IJmuiden – given the new large sea lock (completed in 2022) and ongoing need to accommodate deeper vessels, having a dedicated high-resolution model of the IJmuiden approach channel would be logical. Even if a standalone IJmuiden model was not historically separate, the high-resolution North Sea coastal models (100 m grid DCSM-FM or earlier "kuststrook" models) effectively cover the area. These models capture the **complex flow patterns around the IJmuiden moles**, including the **flow separation and recirculation** zones. Field studies have shown that the IJmuiden breakwaters cause converging and diverging tidal streams: as the flood tide flows northward along the Holland coast, it splits around the harbor, creating a large eddy north of the port during flood and another south of the port during ebb [7]. The flow contraction at the narrow harbor mouth leads to locally enhanced currents (and even a permanent scour hole seaward of the breakwater tips) [20]. **Figure 1** below illustrates these tidal current patterns near IJmuiden, including the eddies and circulation cells in the lee of the breakwaters:

Fig. 1: Schematic of converging and diverging tidal currents around the IJmuiden harbor entrance (adapted from Van Rijn 1995). Flood tide produces a large clockwise eddy north of the harbor, while ebb tide creates a counter-clockwise eddy to the south. Such flow patterns lead to strong cross-currents at the channel entrance and require careful timing of ship movements.

Rijkswaterstaat's models are used to **predict these currents under various conditions** – not just tides, but also storm surges and wind-driven flows. During storm conditions, cross-currents can be further exacerbated by surge-induced flow or seiche effects in the canal. The operational modeling systems (often running on the Delft-FEWS platform, discussed later) assimilate meteorological forecasts (e.g. wind fields, pressure from the Dutch weather service or ECMWF) to predict the surge component, which combined with tides yields total currents. For example, RWS has developed models that incorporate atmospheric influence on currents, filling the gap beyond harmonic tide predictions [21]. The output includes current speed and direction forecasts at strategic locations (like buoy IJMuiden Outer or specific ranges along the channel). In summary, **RWS and affiliated agencies rely on physics-based 2D/3D models as a foundation** for predicting cross-currents affecting navigation. These models provide the baseline forecasts that pilots use to decide when a deep-draft ship can safely transit the IJmuiden locks without excessive drift.

Looking ahead, RWS is updating its model arsenal to the new flexible mesh models (D-Hydro) and increasing model resolution to better resolve localized phenomena like harbor circulations. Yet, even as these models improve, there is an increasing interest in leveraging **machine learning** techniques to enhance current predictions – either by post-processing model outputs or by accelerating computations. In the next sections, we explore how ML can complement or even replace components of traditional flow models.

Machine Learning Enhancements to Flow Modeling

Classical hydrodynamic models are powerful, but they face challenges in accuracy and efficiency. Simplifications are inevitable – e.g. using a single friction coefficient to represent seabed roughness over a wide area, or assuming uniform eddy viscosity, etc. These **parametrizations** mean certain subgrid processes aren't perfectly captured [22]. Moreover, high-fidelity models (fine grid 3D models with many layers) can be **computationally slow** – sometimes too slow for real-time use. As an example, a detailed urban flood model might take 16 days to simulate 24 hours of flooding [23]! Even in simpler cases, running an unsteady 3D model for a week-long forecast might take hours, which limits the ability to do many scenario runs or ensembles. Recognizing these issues, there's a push to employ **machine learning** (especially data-driven approaches like neural networks) to improve predictive performance:

- **Speeding up simulations (Surrogate Models):** ML can learn to emulate the behavior of a physical model, acting as a fast surrogate. Once trained on simulation data or historical observations, an ML model (like a neural network) can produce results in milliseconds that approximate what a numerical model would take hours to compute. For instance, researchers have trained **physics-informed neural networks (PINNs)** as surrogates for hydrodynamic simulators – in one study, a PINN was applied to emulate Delft3D-Flow results for fluvial flooding scenarios [24]. By embedding the physics (the differential equations) into the training, PINNs can achieve reasonable accuracy while being orders of magnitude faster at runtime. Similarly, convolutional neural nets (CNNs) have been used to **predict flood inundation maps** given inputs like rainfall and tide, essentially learning to reproduce the outputs of a 2D flood model without solving the full PDEs each time. An example from the UK: a complex Integrated Catchment Model for Eastbourne (with rivers, tides, etc.) was replaced by a CNN that can simulate flood extents *in seconds rather than days*, enabling real-time flood warning at fine spatial scales [23]. Such surrogates could be applied to coastal current modeling – e.g. a neural network could learn the mapping from tide, wind, and surge conditions to a **current speed at IJmuiden** (or a spatial current field), bypassing the need to run a WAQUA model every time.

- **Improving accuracy (Data-driven corrections and hybrid models):** Another role of ML is to **learn complex nonlinear relationships** that a simplified physical model might miss. By training on large datasets of observations (and possibly model outputs), ML models can identify patterns and corrections. Importantly, they can also incorporate real-time data to adjust forecasts. For example, RWS often does bias-correction on water level forecasts using statistical methods; ML can take this further by learning the error characteristics of the model under various conditions. In practice, **hybrid modeling** – combining process-based models with ML – has shown **superior performance** in some cases. A recent Deltares study on wave forecasting demonstrated that augmenting a wave model (SWAN) with an ML component reduced forecast errors by 30–40% [25] . The ML was likely used to adjust the model's output based on historical discrepancies, resulting in more accurate 48-hour wave predictions. In a currents context, one could similarly train an ML model to correct a hydrodynamic model's output: for instance, given model-predicted and observed currents for past events, a neural net could learn to adjust the model forecast (accounting for factors like local wind gusts or stratification that the model under-resolves). This hybrid approach leverages the strengths of physics (physical consistency, ability to extrapolate to novel forcings) and data (capturing real-world effects and reducing bias). Deltares researchers have indeed advocated linking process-based and ML models, noting that it **"significantly increases the accuracy of operational forecasts"** compared to using either alone [25] .

- **Replacing specific model components:** ML can also be used within a modeling pipeline to replace or enhance certain components. For example, in a 3D hydrodynamic model, the turbulence closure or bottom friction could be tuned by an ML model that learns from data (this borders on the concept of **self-learning physics models**). Another avenue is using ML for **downscaling**: a coarse model provides a large-scale flow, and an ML model then downscales that to finer spatial resolution in a local area, essentially learning the local flow patterns (this could be valuable for high-resolution harbor flows without running a costly fine-grid model in real time).

- **Forecasting beyond physics:** Some phenomena affecting currents might not be fully captured by hydrodynamic equations alone – for instance, unpredictable short-term flow reversals due to eddy shedding, or human operations (like lock discharges). ML can be trained on direct data (e.g. from ADCP current measurements or radar surface current maps) to make short-term **nowcasts** of currents that complement the physics model. These pure data-driven models (like an LSTM – Long Short-Term Memory recurrent neural network) can assimilate time series of recent observations and forecast a few hours ahead, potentially outperforming a coarse model in the nowcasting range.

A key advantage of ML noted by practitioners is **speed for real-time forecasting**. Traditional models, as mentioned, can be too slow for urgent predictions. JBA Consulting highlights that ML models "can often produce forecasts faster, enabling real-time warnings and decision-making" [26] . They also point out that ML can handle uncertainties better: physical models typically provide one deterministic outcome per run, whereas ML models (especially if used in an ensemble or probabilistic framework) can more easily produce a range of outcomes or update forecasts rapidly as new data arrives. On the flip side, one must be cautious: ML models require **large quality datasets** for training, and they might struggle outside the range of conditions they've seen. Pure ML models also lack the built-in guarantees of physical consistency (e.g. mass conservation) that a physics-based model has. This is why hybrid approaches (physics-informed ML or ML used as a supplement rather than a sole predictor) are popular in water management.

In summary, machine learning offers tools to **enhance hydrodynamic current predictions** in two main ways: by **accelerating computations** (making models feasible in operational contexts where speed is essential) and by **improving accuracy** (learning and correcting systematic model errors or capturing omitted physics). The next section provides concrete examples of projects where these approaches have been implemented, illustrating the real-world benefits in coastal and estuarine environments.

Case Studies: Combining Machine Learning and Hydrodynamic Models

To ground the discussion, we present several case studies and projects (primarily European) that integrate ML with traditional flow models for coastal or estuarine current predictions and related applications:

- **LSTM River Level Forecasting (UK)** – In Derbyshire, UK, an ML model was used to forecast water levels on the River Doe Lea to protect a construction site [27]. A Long Short-Term Memory (LSTM) network was trained on a large database of rainfall and river flow records (66 catchments worth of data, later fine-tuned to the local site). The LSTM essentially replaced a rainfall-runoff hydraulic model. Results: the ML model significantly outperformed the traditional model in predicting small-scale flood peaks. Over a 1-year test, it would have **prevented 15+ false flood alerts** (which the traditional model would have triggered) while still capturing all real flood events [28]. This model was **deployed operationally through Delft-FEWS** – demonstrating that such ML models can be plugged into a standard forecasting system [29]. Although this example is riverine, the principle extends to coastal water levels and currents (which often also use data-driven stage forecasts). It shows that ML can reduce false alarms and improve reliability in forecasting.

- **Tidal Surge Prediction with ML (Thames Estuary, UK)** – Another project by the same team focused on the Thames Barrier in London, which relies on accurate tide and surge forecasts. The existing system used a 1D hydraulic model of the tidal River Thames. An LSTM was trained on observed tide levels, model simulations, river flow, and wind to predict water levels along the estuary [30]. The **LSTM model dramatically improved accuracy**: for example, at Silvertown (near the Barrier), 92% of high-tide forecasts were within ±0.1 m error using the LSTM, compared to only 68% within ±0.1 m using the physics-based model [30]. By reducing uncertainty, this ML-enhanced forecast could help avoid unnecessary Barrier closures (each closure is costly and strains the infrastructure). This is a great example of using ML to **calibrate and improve a physical model's output** – effectively learning the complex response of the estuary to coastal surge and local meteorology better than the coarse model. It highlights the benefit of hybrid forecasting: the ML used outputs from the physical model as one input among others, combining model physics with data learning.

- **Neural Network Surrogate for Urban Flood Model (Eastbourne)** – Mentioned earlier, Eastbourne's integrated model (including coastal tide, waves, river, and sewer flooding) was far too slow for real-time use (16 days per day of simulation). Researchers trained a **CNN-based surrogate** to emulate this model's behavior [23]. The surrogate takes in rainfall forecasts, tidal conditions, etc., and outputs predicted flood extents/water levels in seconds. Moreover, they incorporated a probabilistic approach to capture uncertainty (issuing probabilities of flooding at postcode level). This is a flood inundation example, but it's closely related to coastal current modeling, as the tidal boundary and coastal inundation are part of it. The success here suggests that for something like **IJmuiden cross-currents**, one could train a surrogate that maps tidal phase and amplitude (plus wind, surge) to the cross-channel current speed at the harbor entrance. Once trained, it could produce a forecast nearly instantly, which could then be updated frequently (say every few minutes with new data) to assist port decision-making. The Eastbourne case, part of a Flood Resilience Innovation Program, shows how ML surrogates can bring what was once an offline planning model into an **operational real-time tool**.

- **Hybrid Wave Forecasting (North Sea)** – Deltares researchers combined a process-based wave model with ML to improve wave height and period predictions for the North Sea [25]. They trained an ML model on an extensive dataset of past model forecasts and observations, and then used it alongside the physics model. The **hybrid approach reduced forecast errors by ~30–40%** [25], greatly increasing 48-hour wave forecast accuracy. Although this is waves (not currents), it's analogous to using ML to post-process a hydrodynamic current model. The success of this project (published in late 2023) underlines that **blending ML with physical models yields tangible improvements** in marine forecasts. Joost den Bieman (Deltares) noted this helps in planning offshore operations and "predicting tide gates for ships" more accurately [31] [32] – implying better combined forecasts of waves, water levels, and currents allow ships to transit at optimal times.

- **Estuarine Salt Intrusion Forecast (Rhine-Meuse delta, NL)** – In 2023, a Dutch research team (Wageningen University & Deltares) demonstrated an LSTM model to predict **saltwater intrusion levels** in the Rhine-Meuse Delta (which includes Rotterdam/New Waterway) [33]. Salt intrusion – essentially the inland penetration of the salt wedge during low river flow and high tides – is a process governed by estuarine circulation, and it's typically simulated by 3D hydrodynamic models (e.g. Delft3D or WAQUA 3D). However, those are computationally intensive to run in forecasting mode. The researchers trained an LSTM on historical data of salinity (chloride concentrations) at various monitoring stations, along with tide, river discharge, and wind data [34]. The LSTM could forecast daily salinity up to 7 days ahead at key locations. It **captured timing of salt peaks well**, though it struggled a bit on exact peak magnitudes for long lead times [35]. They report performance metrics like precision and recall of around 0.7–0.9 on short leads, decreasing as lead time grows [36]. This case is notable because it deals with **3D physical dynamics (density-driven flow)** purely with a data-driven model. It shows that with sufficient data, ML can approximate complex estuarine dynamics enough to give useful forecasts, which water managers can use to decide on mitigation measures (like flushing with fresh water or closing barriers). A similar approach could conceivably be applied to *current* profiles or surface currents in an estuary.

- **FloodWaive Project – 2D Deep Learning Flood Model (Germany)** – In a recent Delft-FEWS community talk (2024), Dr. Julian Hofmann presented "DeepWaive," a generalized deep learning approach to 2D flood simulation [37]. His team developed a model that takes precipitation or river discharge inputs and **directly outputs spatial flood extents and depths**, learned from many runs of a hydraulic model. DeepWaive essentially bypasses running a 2D shallow-water model each time, providing results in seconds [38]. While the focus was on river and flash flood scenarios, the method is equally applicable to coastal surge flooding or predicting current speed maps. The fact that this was shared with the Delft-FEWS community indicates strong interest in integrating such AI-driven models into operational forecasting workflows.

These case studies collectively highlight a trend: **hybrid and ML approaches are transitioning from research to operations** in the water domain. They deliver faster and/or more accurate predictions for floods, tides, and currents. In the context of IJmuiden and similar coastal sites, we see potential in: (a) using ML to refine model-based cross-current forecasts (e.g. an ML model could learn to adjust the timing and magnitude of peak cross-current based on comparing model predictions to past ADCP measurements in the channel), and (b) using ML surrogates to allow high-resolution predictions on the fly (e.g. a quick predictor of the entire 2D flow field around the harbor for a given tide and wind). Each approach has pros and cons, which we analyze next.

Physical vs. ML vs. Hybrid Approaches: A Comparative Analysis

It is instructive to compare pure physical modeling, pure machine-learning modeling, and hybrid combinations in terms of strengths and limitations:

- **Physics-Based Models (Deterministic Hydrodynamic Models):** These rely on first-principles equations and well-established numerical methods. **Advantages:** They are *physically interpretable* – every output (currents, water levels) is linked to a known physical process, and conservations laws (mass, momentum) are respected. This makes them reliable in scenarios outside the range of past observations, as long as the physics is correctly set up. For example, a 3D model can predict currents for an unprecedented combination of tide + storm surge, providing insight into conditions with no direct historical precedent. The results can also be diagnostic – showing *why* currents behave a certain way (e.g. through flow vectors, pressure gradients, etc.). **Disadvantages:** They require accurate input data and calibration; small errors in boundary conditions (winds, upstream flows) or parameters (roughness, viscosity) can lead to significant output errors [39]. They also simplify reality (e.g. assuming a single roughness for a large area that actually has varying seabed types [22]). Critically, they can be **computationally demanding**, especially high-resolution 3D runs – sometimes too slow for real-time use [40]. There's also the issue of *single deterministic output* – a given model run produces one scenario, and capturing uncertainty requires running multiple simulations (further compounding the computational load). In summary, physical models are trustworthy within their validated scope but can struggle with local accuracy and speed.

- **Data-Driven ML Models:** These forgo explicit physics and instead learn from data. **Advantages:** If provided with enough quality data, ML models can *capture complex nonlinear relationships* that might be impractical to fully model (for instance, an ML might infer how a certain wind pattern coupled with a particular tidal phase causes an anomalously strong cross-current in a specific channel segment – something a coarse grid model might miss). They tend to be extremely fast at runtime – computing a matrix of weights and activations is trivial compared to solving PDEs. This allows **rapid updates and ensemble forecasts**, giving probabilities of exceedance or quick what-if analyses. ML can also integrate disparate data types seamlessly (e.g. water level, current, wind, even vessel GPS drift data) to improve predictions. **Disadvantages:** ML models often act as "black boxes." They provide a prediction but not a mechanistic explanation. Traditional ML "models rarely describe an interpretable data-generating process" [41] – unlike a Navier-Stokes model, which *is* a mechanistic description. This lack of interpretability can be a hurdle for trust in safety-critical forecasting (though explainable AI methods are emerging to probe ML decisions). Another major limitation is **generalization**: ML models can fail if conditions move outside the range seen in training data. For example, an ML current predictor trained on moderate weather might be unreliable in an extreme storm if such a storm wasn't in the training set. They also need continuous data updates and can drift if the underlying system changes (e.g. bathymetry changes due to dredging could invalidate an ML model unless retrained). Essentially, ML excels when *ample data covers the scenarios of interest*, and it can struggle otherwise. There's also a maintenance aspect – retraining and validating ML models needs to become part of the operational workflow.

- **Hybrid Approaches (Physics + ML):** These attempt to get the best of both worlds by either coupling ML into the model or using ML around the model. **Advantages:** Hybrids can enforce physical consistency at a high level (via the model component) while letting ML handle the parts that are uncertain or highly nonlinear. For example, one can run a coarse physical model for general pattern and use ML to "downscale" or correct it, ensuring that fundamental tides are right (from physics) but small-scale biases are fixed (by data-driven learning). This often yields **improved accuracy** – as seen, hybrid wave models had 30%+ error reduction [25], and a combined tide+ML approach improved tide predictions in the Thames drastically [30]. Another advantage is efficiency: using ML to replace only the heavy components (say, replace a detailed local model with an ML proxy) can speed up forecasting without throwing away the larger-scale physical context. **Disadvantages:** Creating a hybrid system can be complex. One must ensure the ML and model components communicate properly and that errors don't amplify. There's also the risk of introducing ML biases into a system that might be hard to debug. From an implementation standpoint, hybrid models still require a lot of data (to train the ML part) and all the setup of a physical model, so they can be resource-intensive to develop. But once in place, they tend to be robust and performant.

In practice, the trend in the Netherlands and Europe is toward **hybrid solutions** for hydrodynamic forecasting. As one article put it, *"machine learning is not a replacement for hydrological expertise – it's a new tool, enabling us to forecast the future more clearly"* [42] [43]. That encapsulates the viewpoint that physics models provide the foundational understanding and consistency, while ML provides the clarity in terms of data-driven corrections and speed.

To illustrate the comparison, Table 2 provides a brief qualitative comparison of these approaches in the context of current prediction:

Aspect	Physical Model Approach	ML Model Approach	Hybrid Approach
Basis	Solve governing equations (continuity, momentum, etc.) with initial/boundary conditions. Outputs are physically constrained.	Learn mapping from inputs to outputs purely from historical data (no explicit physics). "Black-box" function approximation.	Use physics model for baseline pattern or constraint, and ML to refine or emulate parts of the solution.
Accuracy	Good if physics and inputs are well-represented; may have biases due to parameterizations or unresolved scales [22].	Can match historical data very closely; captures local effects the model might miss. May struggle with unseen conditions or long-term consistency.	Often highest accuracy: ML corrects systematic model errors [25], model prevents unphysical ML outputs. Many studies report error reductions with hybrid vs either alone.

Aspect	Physical Model Approach	ML Model Approach	Hybrid Approach
Speed	Moderate to slow. High-res 3D runs can take hours or days, making rapid updates difficult [40]. Faster for 1D or coarse 2D models.	**Fast.** Once trained, predictions are virtually instantaneous, enabling real-time forecasting and ensembles. Training can be time-consuming but is done offline.	Faster than pure physics (since ML can replace heavy components), though possibly a bit slower than pure ML if model still runs. Still suitable for real-time if designed well.
Data Requirements	Needs boundary forcing (tides, wind) and calibration data for tuning parameters. Does not "learn" from data on its own beyond calibration.	**Data-hungry.** Requires large, diverse training dataset of past events (observations or high-fidelity model runs). Performance hinges on data quality and representativeness [44].	Requires both: a physics model setup *and* data to train/guide ML. Can sometimes use model-generated data to train ML (e.g. model as a data generator for ML), reducing reliance on observed data.
Generality	Can be applied to new scenarios (climate change, novel events) as long as physics still holds. Extrapolation is a strength of physics (within limits of assumptions).	Limited to interpolation within the domain of training data. Extrapolation to novel scenarios (new extremes, different configurations) is risky without retraining.	Improved generality over pure ML. The physics part can handle novel large-scale conditions, while ML corrects finer details within known regimes. Still need caution if truly outside both model and data experience.
Explainability	High – each result comes from known physical reasoning. Easier to communicate to stakeholders (e.g. "the current is strong because of the pressure gradient from storm surge"). [45]	Low – difficult to explain why the model output a certain current value except via complex analysis of network weights. Less transparent decision-making [45].	Medium – core behavior is explainable via physics; ML adjustments can be harder to explain, but since they are relatively small corrections or patterns, analysts can often still reason about results in physical terms.

Aspect	Physical Model Approach	ML Model Approach	Hybrid Approach
Maintenance	Involves periodic recalibration (if conditions change) and updates to model (e.g. grid or bathymetry updates). Generally stable once set up.	Requires ongoing maintenance: retraining when new data comes or when system changes, monitoring for drift. Essentially an evolving model that must be kept aligned with reality.	Dual maintenance: update physical model as needed and retrain ML as new data accumulates. Tools and frameworks are emerging to automate this (continuous learning). The synergy can make the system more robust to change (e.g. ML can adapt faster to a sudden change if retrained, whereas a physical model would need re-calibration).

In essence, **physical models vs. ML is not an either/or** proposition. They complement each other. For cross-current predictions in navigation, a feasible strategy is to use the physics-based model to simulate the broad conditions (tide, surge, density flows) and use ML to fine-tune the local cross-current estimates (which could depend on high-resolution bathymetry, small-scale eddies, etc., learned from data). The hybrid approach can achieve the accuracy needed by port authorities (who often require very low prediction errors for operational decisions) while still respecting the underlying physics and offering reliability under unforeseen events.

Integrating ML-Enhanced Models into Operational Systems (e.g. Delft-FEWS)

Implementing the advanced approaches above in day-to-day forecasting requires integration into operational platforms. One widely used platform is **Delft-FEWS** (Flood Early Warning System), an open-source forecasting data management system developed by Deltares and used by RWS (and many agencies worldwide). Delft-FEWS is essentially a modular framework that orchestrates data import (e.g. weather forecasts, water level observations), model execution, and dissemination of results [46]. It was designed to be model-agnostic ("a data-centric open shell" [47]), meaning it can host different models and scripts as part of the forecasting workflow.

Integrating ML models into Delft-FEWS or similar systems can be done in multiple ways:

- **As a custom model adapter:** FEWS allows custom modules (often via XML configuration) that can call external executables or scripts. An ML model, for example a Python script loading a trained neural network, can be invoked at a certain step in the workflow. It could take as input the latest water level forecast time series from a physics model (available in FEWS database) and output a corrected time series. This output can then be fed into subsequent modules (or directly to the user interface as the official forecast). The **JBA LSTM deployment** is a concrete example – they trained an LSTM externally and then implemented it within Delft-FEWS to produce operational river level forecasts [29] . From the user perspective, it runs like any other model in the FEWS forecasting chain, but under the hood it's a neural network making the predictions.

- **Standalone ML forecast integrated as a data source:** In some cases, an ML model might be running continuously outside FEWS (for instance, a cloud service that updates a forecast every 15 minutes from live data). FEWS can be configured to simply fetch that forecast (via an API or file exchange) and incorporate it into the dashboard. This is more of a data integration than running the model internally, but it achieves the same end – forecasters see the ML-enhanced prediction alongside or combined with traditional model results.

- **Hybrid model inside FEWS:** FEWS workflows can include multiple models in sequence. For example, one could have FEWS run a coarse WAQUA model first, then automatically pass its results to a Python ML script for refinement, then combine the output. Because FEWS is highly configurable, one can set up these sequential steps without hard-coding. The **FEWS-Python API** or general adapter can facilitate this. Deltares has documented use of FEWS with external tools (e.g. integrating HEC-RAS, as per search result [15†L19-L27]) and the principle is similar for ML models.

- **Real-time updating with data assimilation vs ML:** It's worth noting that operational systems traditionally use data assimilation (e.g. Kalman filters) to update model forecasts with observations. ML approaches like neural nets can be seen as more flexible nonlinear assimilators or forecasters. In FEWS, one could replace or supplement a data assimilation module with an ML module. For instance, instead of a linear bias correction, a pre-trained random forest or neural net could adjust the model state based on recent observations.

From an **implementation framework** perspective, key considerations include: **computing resources** (ML models are usually lightweight to run, often just matrix multiplications, which is trivial compared to running a full hydrodynamic model; they can even be executed on GPUs if needed for speed, but for a few locations or moderate grid, CPU is fine), **reliability and fallback** (operational systems need a fallback if the ML model fails or produces outlier results – often the fallback is to revert to the original physics model output or climatology), and **monitoring** (setting up monitoring of model performance, so if the ML starts showing bias due to changing conditions, operators are alerted to retrain or recalibrate).

The **Delft-FEWS 2025 release notes** and user community have already been discussing AI integration. In a recent FEWS Community Talk (Oct 2024), the focus was explicitly on "the application of AI in flood forecasting" [48] . Presentations like those on DeepWaive and ECMWF's AI weather model (AIFS) indicate that FEWS users are actively working on incorporating these new tools. RWS and Deltares are likely exploring how to include ML-based **"advisors"** in the Dutch forecasting system RWsOS – for example, an AI module could advise on storm surge bias correction or rapid inundation mapping.

Finally, beyond Delft-FEWS, other operational systems (like the UK's flood forecasting system or US NOAA frameworks) are also being adapted for AI. The trend is to create an **"ML plugin"** architecture where a trained model can be dropped in with minimal fuss. Given that Delft-FEWS is widely used in the Netherlands (for coastal surge, rivers, water quality, etc.), it will likely serve as the backbone for deploying ML-enhanced cross-current predictions at IJmuiden. The successful deployment by JBA (LSTM in FEWS for river flows) sets a precedent that can be replicated for tidal currents. One can imagine the IJmuiden case: FEWS takes the DCSM-FM model's current forecast at the IJmuiden channel, then applies a neural network (trained on local current meter and wind data) to adjust that forecast to the specific point in the fairway where cross-current is measured. The adjusted forecast is then shown to the duty harbor pilot. All this can happen within minutes and be updated frequently, providing a robust decision-support tool.

In conclusion, **operational integration is very feasible** – the technology (like Delft-FEWS) supports it, and early adopters have demonstrated the benefits. The key steps are training the ML models on historical data, validating them rigorously, and then configuring the forecasting system to include them. With Dutch and European agencies heavily investing in digital twins and smart forecasting, we expect to see more ML-augmented hydrodynamic forecasts in use. For IJmuiden, this means even more accurate and timely predictions of cross-currents, leading to improved navigational safety and efficiency for the Port of Amsterdam.

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