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The development of a fast-computing emulator to predict dike failure during severe flood events

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Abstract

Flooding is one of the most damaging and frequent natural hazards in the world and it is expected that flood events will affect even more people in the future due to climate change, land use change and population growth. The use of proper evacuation schemes has the potential to reduce the consequences of a flood event, i.e. reducing the damage and the number of life-losses and cattle-losses, in areas at risk significantly. Typically, sophisticated two-dimensional (2D) hydraulic models are used to simulate flood propagation of severe flood events to inform flood management decisions. Although these models have proven to be accurate in predicting flood wave propagation and inundation extents in areas with complex dynamic interactions, these models cannot be used for short-term flood forecasting due to the high computational demands and long simulation times. For this reason, emulators (e.g. artificial neural networks (ANNs)) have gained much attention in recent years. In this study, we set up neural networks that are able to predict the dike failure locations during flood events and corresponding outflow hydrographs, based on discharge measurements at an upstream gauge station. These outflow hydrographs can be used to predict the potential inundated areas, enabling evacuation of the people in the areas at risk on time.

Keywords: Flood forecasting, Hydraulic modelling, Neural network, Dike failures, Conceptual modelling

1. INTRODUCTION

Flooding is one of the most damaging and frequent natural hazards in the world. They account for half of the weather-related disasters between 1995 and 2015 (Verwey et al., 2017) and it is expected that flood events will affect 1.3 billion people globally by 2050 (Ligtvoet et al., 2014) due to climate change, land use change and population growth. In recent times, we have seen a switch in flooding policy from reducing flood probabilities by constructing large flood defenses to decreasing flood risk by proper management strategies all over the world (Krupka et al., 2007). This new approach aims at reducing the consequences of a flood event. The use of proper evacuation schemes has the potential to reduce these consequences, i.e. reducing the damage and the number of life-losses and cattle-losses, in areas at risk significantly. A dike failure may cause severe inundations in the hinterland, depending on the exact failure location (Bomers et al., 2019a). Therefore, an overview of the dike sections most likely to fail is required to be able to take proper evacuation measures. It is crucial to communicate the evacuation plans on time since human behavior during an emergency is generally chaotic and hard to control (Simonovic & Ahmad, 2005).

Typically, sophisticated two-dimensional (2D) hydraulic models are used to simulate flood propagation of severe flood events to inform flood management decisions (e.g. Bomers et al. (2019a), Leandro et al. (2014), Moya Quiroga et al. (2016)). These types of models are based on the conservation of mass and momentum in a 2D plane using the shallow water equations. Although these models have proven to be accurate in predicting flood wave propagation in areas with complex dynamic interactions, these models cannot be used to predict the most vulnerable dike sections in real-time due to their high computational demands and long simulation times (e.g. Bomers et al., 2019b). Therefore, in this study, we aim to set-up artificial neural networks (ANNs), i.e. emulators, that are able to predict the most vulnerable dike sections in less than a second based on an upstream measured hydrograph. ANNs are data-driven models trained based on the input-output relations of a physically-based model or field measurements. This type of emulator has as advantage that it is able to reproduce complex nonlinear behavior between the input and targeted output. This is one of the reasons why emulators are already commonly applied in the field of hydrology (Razavi et al., 2012). However, no emulators exist that can predict both fast and accurately the dike failure location, timing and outflow volume in case of an extreme flood event, while these parameters are the main drivers of the total flood damage during a flood event. In this study, two dike failure locations in a complex river delta system with multiple bifurcations are considered. By including two potential dike failure locations, the developed emulators should be able to capture the interrelated effects of a dike failure on downstream water level reductions and corresponding dike failure probabilities of the downstream potential dike failure section.

The outline of this paper is as follow. In section 2 the case study and model are explained that are used to create the training data to be able to set up the emulators, described in section 3. The results are presented in section 4. In section 5 we address the capabilities of emulators and compare their potential with the more established conceptual modelling approaches. The paper ends with the conclusions presented in section 6.

2. CASE STUDY AND CREATION OF THE TRAINING DATA

2.1 Case Study

The Dutch Rhine river delta is used as a case study. The Rhine river originates in the Alps in Switzerland and flows through Germany towards the Netherlands. The Rhine river enters the Netherlands near Lobith, where after it bifurcates into the Waal river (~2/3 of the discharge at lobith) and the Pannerdensch Canal (~1/3 of the discharge at Lobith). The Pannerdensch Canal subsequently bifurcates into the Nederrijn river (~2/9 of the discharge at Lobith) and IJssel river (~1/9 of the discharge at Lobith) (Figure 1). In the study area, floods mainly evolve during winter periods due to heavy precipitation events in combination with frozen or saturated soils in the upstream parts of the river basin. Dikes are situated along the Dutch Rhine river branches to protect the hinterland from being flooded. These dike sections may fail during flood events, influencing water levels in the river delta system which may consequently also influence the discharge distribution along the various river branches (Bomers et al., 2019a).

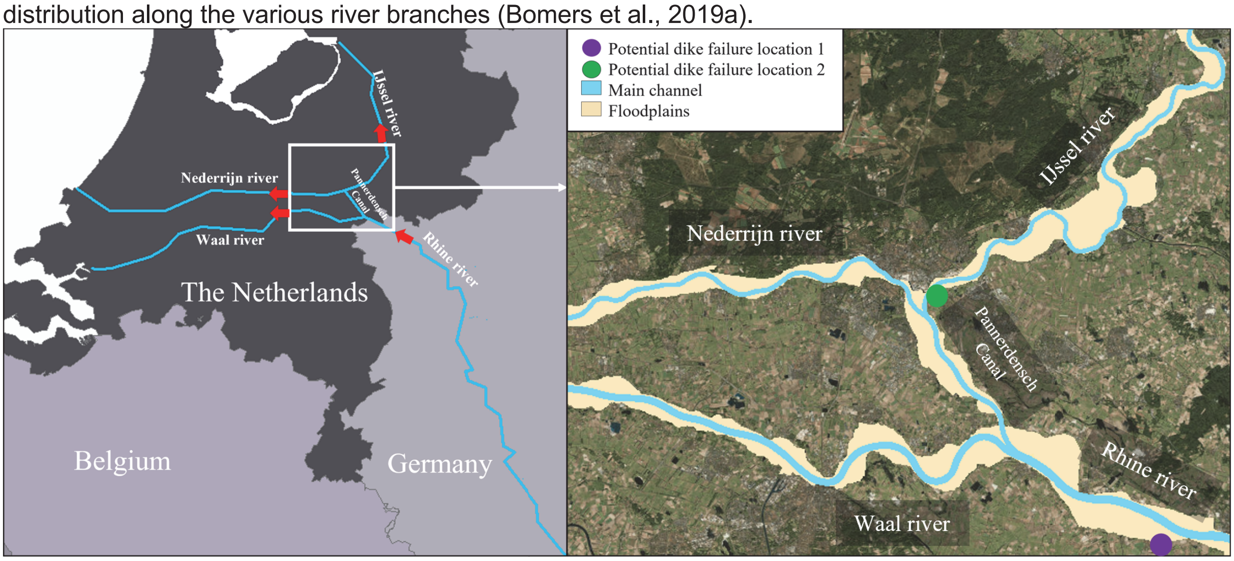

Figure 1. Left figure: The Rhine river delta with the study area given by the white box. Right figure: Close-up of the study area including the two potential dike failure locations.

2.2 Training Data

Since no recent dike failures have occurred in the study area, a hydraulic model is used to create the training data that enables the set-up of the fast-computing emulator. The digital elevation model and land use classes including corresponding roughness values were provided by the Dutch Ministry of Infrastructure and Water Management and the Landesamt für Natur, Umwelt und Verbraucherschutz (LANUV) of Northrhine-Westfalia. A one dimensional-two dimensional (1D-2D) coupled model is used in which the river system (main channel and floodplain) are simulated by 1D profiles, while the hinterland is discretized on a 2D grid to accurately simulate the flood inundation patterns caused by the dike failures (Figure 2). The upstream boundary is located at Emmerich, Germany, where a discharge wave is used as boundary condition. Normal depths are used as downstream boundary conditions (Brunner, 2016). HEC-RAS (v. 5.0.3), developed by the Hydrologic Engineering Center (HEC) of the US Army Corps of Engineers, is used to simulate the flood events used as training data by solving the diffusive wave equations.

The 1D profiles and 2D grids are connected by a structure corresponding with the locations of the dike sections along the various river branches. Model calibration was performed by altering the main channel friction, until simulated water levels were close to measurements. The 1995 Rhine river flood event, representing the most recent flood event and having a return period of around 60 years, was used for model calibration. In total, 14 gauge stations are present in the model domain and the maximum water levels were predicted with an average deviation of 1 cm compared to measurements after model calibration. Validation was performed with the 1993 flood event, having a return period of around 30 years. A deviation of less than 7 cm in simulated maximum water levels compared to measurements was found among the 14 gauge stations. Furthermore, the discharge partitioning along the Dutch Rhine river branches was predicted with high accuracy, only deviating 3.7% from measurements on average.

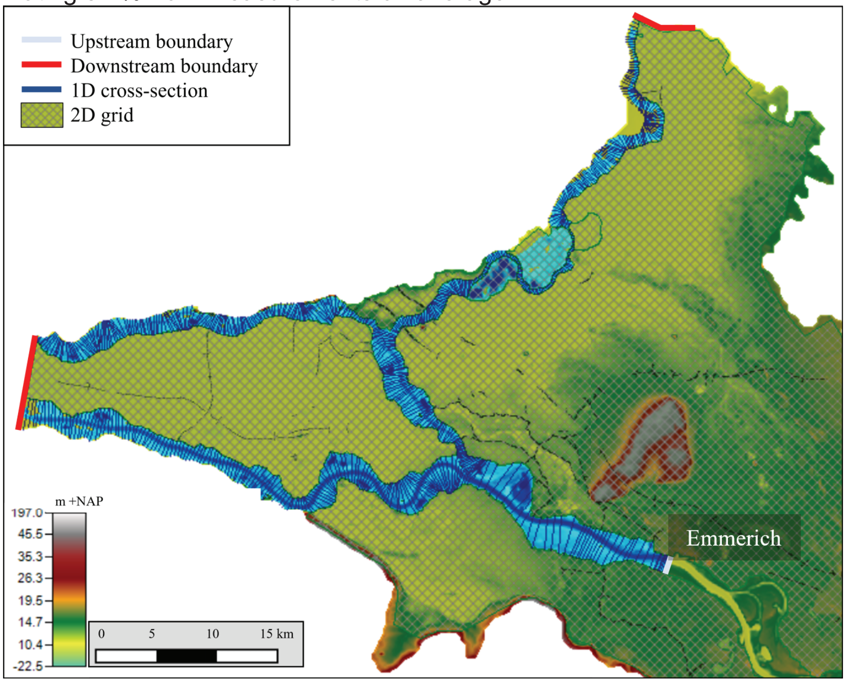

Figure 2. The one dimensional-two dimensional coupled hydraulic model used to generate the training data.

To generate the training data, two potential dike failure locations are included in the analysis (Figure 1). It is assumed that these dike sections only fail due to the failure mechanism overflow, i.e. if the simulated water level is equal to the dike crest level. Furthermore, it is assumed that the dikes immediately breach to the level of the natural terrain and a constant breach width of 150 m is considered. The remaining dike sections are modelled as infinitely high dikes such that water only leaves the river system through one of the two dike failure locations. Additional overflow is not included in the analysis to reduce the complexity of the system. Furthermore, the upstream discharge waves, both in terms of hydrograph shape and peak value, are varied to create a wide range of potential flood event scenarios. In total, 80 flood events are simulated with the 1D-2D coupled hydraulic model. The upstream discharge waves are based on GRADE (Generator of rainfall and discharge extremes), which has a large data set of realistic flood event scenarios under current climate conditions (Hegnauer et al., 2014). From this data set, 80 discharge waves were randomly selected. In the Dutch water policy, a maximum design discharge is considered corresponding to a return period of 100,000 years, corresponding to a peak value of between 16,500 and 19,300 m^3/s near Lobith (Bomers et al., 2019c). This range is used to scale the 80 GRADE discharge waves in terms of its peak value. These upstream discharge waves are considered to be the input data of the fast-computing emulator, developed in section 3, while the resulting outflow hydrographs at the two potential dike failure locations are considered to be the targeted output.

3. The fast-computing emulator

In this study, we focus on the development of neural networks since they have shown to be highly accurate in predicting water levels during flood events (e.g. Kia et al. (2012), Peters et al. (2006), Shrestha et al. (2005)), as well as in predicting breach outflow hydrographs at a single locations (e.g. Hooshyaripor et al (2015), Nourani et al. (2012)). More specifically, we develop a nonlinear autoregressive - with external input - (NARX) neural networks since the prediction of a time-varying output based on an input time series is required. A NARX is a recurrent dynamic neural network with feedback connections suitable for time series predictions (Wunch et al., 2018). It predicts a time series y(t) based on *d* past values of y(t) and an input time series x(t). In this study, a NARX neural network is develoepd for both potential dike failure locations in which the upstream discharge wave is used as input time series and the outflow hydrograph at the dike failure location as targeted output time series.

The MATLAB Deep Learning Toolbox 14.1 is used to develop the two emulators. A feed-forward network is developed, meaning that the information in the neurons flows from an input layer (the upstream discharge wave) through a hidden layer with a number of neurons (determined during the training phase) to an output layer (the outflow hydrograph at the dike failure location). The hyperbolic tangent sigmoid activation function is used to compute the output time series based on the weighted sum of the input since a sigmoid activation function can introduce nonlinear behavior to the network (Peters et al., 2006). During the training phase, it was found that the emulators produce most reliable results for two neurons in the hidden layer and two time step delays *d*. The Levenberg-Marquardt algorithm was used to avoid overfitting, meaning that the emulator fits the noise existing in the training data rather than the underlying system behavior (Razavi et al., 2012). During the training phase of the two emulators, the training data set created with the hydraulic model was randomly divided into three sets: training (60%) used to train the emulators, validation (20%) used to test whether increasing the data set during the training phase results in more reliable outputs, and testing (20%) used to validate the emulator performance after being trained based on an independent data set. The mean squared error (MSE) was used as a loss function to ensure that the errors in the estimates of the maximum outflow discharge are more heavily weighted than the errors in the smaller values. The accuracy of the two developed emulators are presented in section 4 using the Nash-Sutcliffe model efficiency coefficient (NSE).

4. RESULTS

4.1 System Behavior based on Hydraulic Simulations

During all hydraulic simulations, the dike section along the IJssel river, from now on referred to as dike failure location 2, failed first at a discharge of around 15,750 m^3/s. The most upstream failure location, dike failure location 1, only failed if the peak of the upstream discharge wave was larger than around 17,100 m^3/s. The shape of the outflow hydrograph at location 1 was solely determined by the shape of the upstream discharge wave. However, this dike failure location significantly effects the outflow hydrograph shape at dike failure location 2, since the most upstream dike failure results in downstream water level reduction and effects the shape of the discharge wave throughout the river system. Since the emulators of both failure locations only have the upstream discharge wave as input parameter, special attention must be paid to the predicted outflow hydrograph at location 2 for the scenarios that also location 1 failed.

4.2 Validation of the emulators

The emulators were developed because of the need of near real-time predictions of potential dike failure locations such that evacuation measures can be taken on time. The 1D-2D coupled hydraulic model had a simulation time around ~10 hours per flood event on a standard PC. The emulators were trained in 5 seconds and after training it was possible to compute the outflow hydrographs of 80 potential flood events at both dike failure locations in less than 0.1 second. The restriction in the development of the emulators is thus the creation of the training data using a hydraulic model. However, once trained, the emulators can be used for real-time flood forecasting purposes. With respect to the reliability of the emulators output, it was found that the emulators respond accurately to the varying upstream discharge waves. For dike failure location 1, an NSE of 0.93 was found while an NSE of 0.96 was found for dike failure location 2. Also, the regression lines, presenting the predictions of the hydraulic model and emulators for each time step, show that the emulators predictions are close to those of the hydraulic model at both failure locations (where the 1:1 line represents a perfect fit) (Figure 3). This shows that the emulator at dike failure location 2 is able to correctly respond to potential dike failures upstream in the river system (dike failure location 1). This behavior is also presented by Figure 4 (subplots b and c) in which the upstream discharge wave resulted in a dike failure at both failure locations 1 and 2.

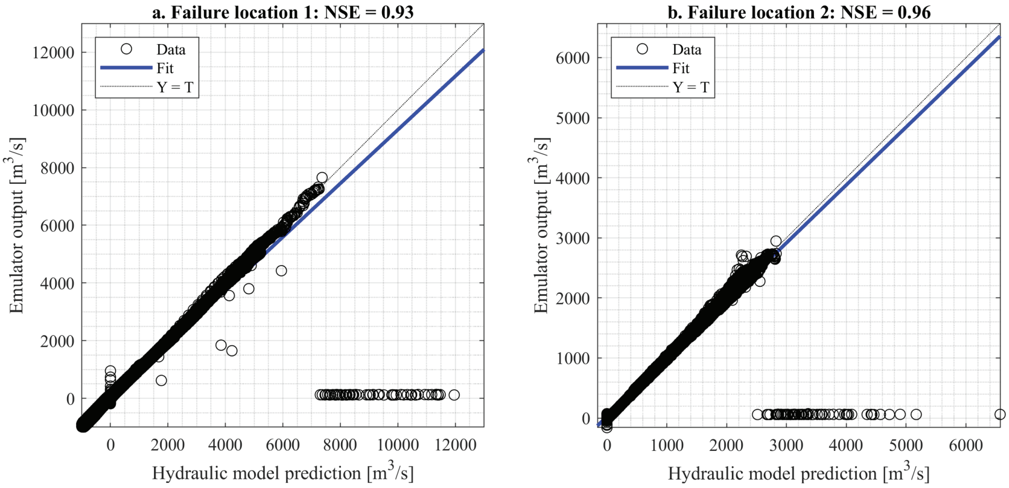

Figure 3. Regression lines showing the deviations in the predicted outflow hydrographs of the two emulators and the hydraulic model. Failure location 1 represents the most upstream dike failure location and failure location 2 represents the failure location at the IJssel river (see Figure 1).

However, some small deviations in model output between the hydraulic model and the two emulators are noticeable. Firstly, in the period before dike failure (hydraulic model out is equal to 0), the emulators always predicts small negative or positive discharges (see Figure 4 and the vertical data points clustered around hydraulic model prediction = 0 in Figure 3). This fluctuating behavior of the emulators is caused by the fact that emulators are very sensitive to any change in the input time series. Since the upstream discharge changes each time step, also the emulator's output changes each time step, resulting in nonzero output values.

Secondly, we found that the emulators predict the peak of the outflow hydrographs one time step later compared to the hydraulic model, explaining the horizontal data points clustered around emulator output = 0 in Figure 3. In this study, a time step of 1 hour was used. The discrepancy between the timing of the dike failure can easily be reduced by decreasing the time step to e.g. 1 minute.

Lastly, the maximum outflow discharges are underpredicted by the emulators (Figure 4). This especially applies for dike failure location 1 (See Figure 4 and the data points representing with discharges larger than 6,000 m^3/s deviating from the 1:1 regression line in Figure 3). However, since underprediction of the peak value only occurs for one time step, the total predicted outflow volumes by the emulators only deviated around 1.5% with the hydraulic model output for both failure locations.

5. CROSSROAD: EMULATORS OR CONCEPTUAL MODELLING?

This study showed that emulators, after being trained with sufficient data, can be used to predict dike failure locations, moment of failure and corresponding outflow hydrographs in real-time. However, not only the outflowing discharge is important to develop proper evacuation schemes, but also corresponding inundation extents and depths. Therefore, in future work, we aim to extend this approach by developing emulators that are able to predict inundation extents and depths based on a measured upstream discharge wave. However, this raises the question of the applicability of emulators as real-time flood forecasting system, especially for the long-term.

A major drawback of emulators is that they require a training data set capturing all relevant uncertainties present in the system. In this work, assumptions were made with respect to the critical water level, the dike breach growth and the final dike breach width. Furthermore, only two potential dike failure locations were considered, while still 80 simulations, equal to 800 hours of simulation time, was required to properly train the emulators. Increasing the complexity of the system by e.g. increasing the number of dike failure locations or considering uncertain critical water levels, requires the need of increasing the training data set. Another disadvantage of emulators is that they are only applicable for the situation they are trained for. If the digital elevation model (DEM) in the hinterland changes over time, due to e.g. the construction of a neighborhood or a heightened highway, the overland flow patterns may change. Therefore, the trained emulator may not be accurate in predicting the inundation extents during a flood event anymore, and consequently the emulator needs to be retrained. This means that all hydraulic simulations needs be performed again with the updated DEM, causing a huge time and computational investment.

These drawbacks of emulators make it questionable whether emulators can be used as real-time flood forecasting system in the future. In contrast, some well-established conceptual modelling approaches for the prediction of inundation extents already exist in literature. These approaches are based on simplified hydraulic concepts that do not attempt to represent the complex dynamic flood generation processes using physics-based mathematical equations, but are still based on the original underlying input data of the hydraulic model. Due to these simplified hydraulic concepts, these approaches are orders of magnitude faster than detailed hydraulic models (McGrath et al., 2018) and have shown to be able to produce near real-time simulations of maximum flood inundation extents and flow depths.

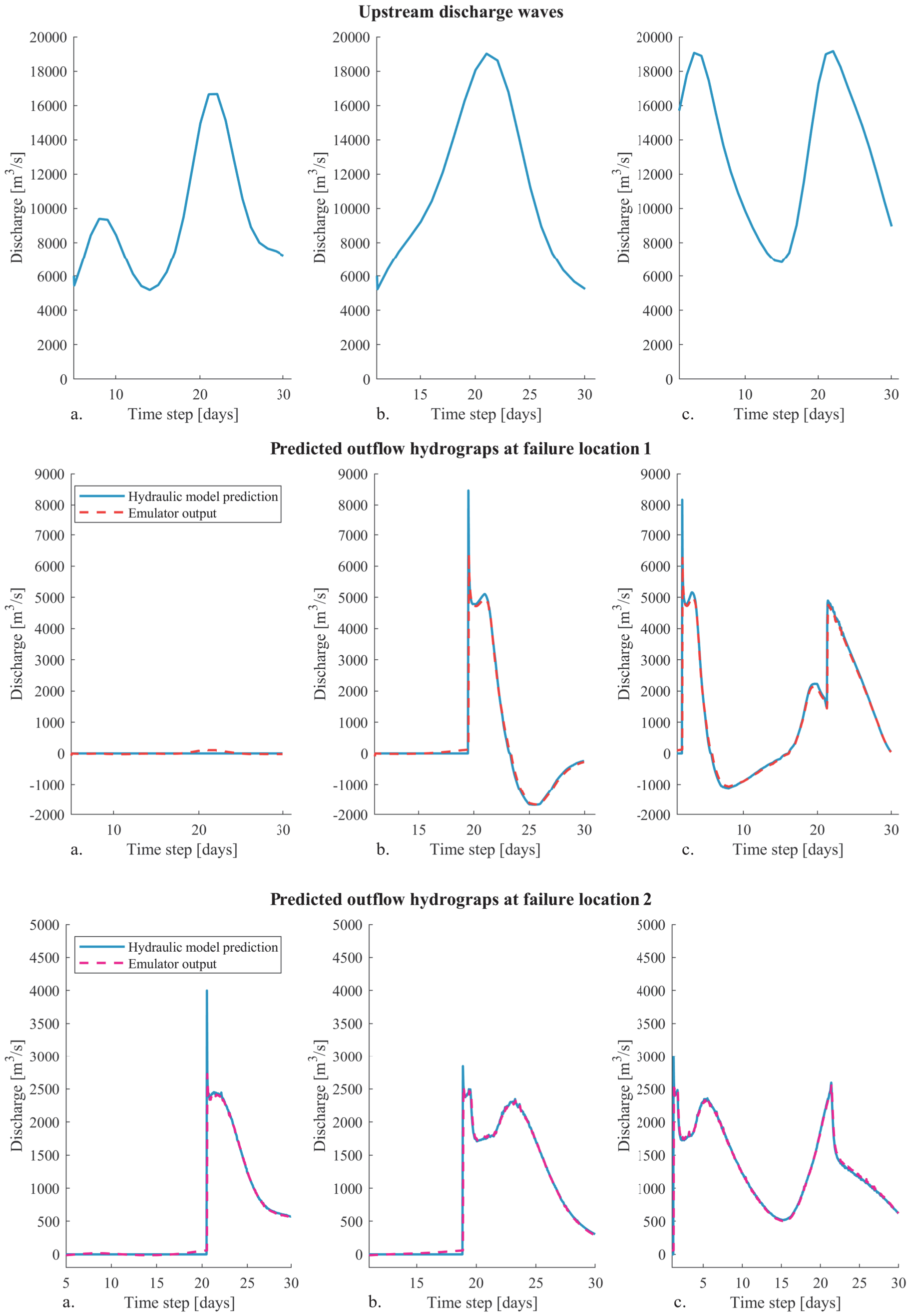

Figure 4. Upstream discharge waves and predicted outflow hydrographs at failure location 1 and 2 by the hydraulic model and emulators. Subplots a. correspond to an upstream discharge wave causing only dike failure location 2 to fail. Subplots b. and c. correspond to an upstream discharge wave causing both failure locations to fail in which subplot b. correspond to an upstream discharge wave with one peak and subplot c. to an upstream discharge wave with two peaks.

An example of such a conceptual modelling approach is the HAND model (Nobre et al., 2011). The HAND model uses the DEM of the hinterland and derives from it the Local Drainage Direction (LDD) which represents, for the application studied in this research, the flow pattern in the hinterland during a flood event.

Based on this drainage direction, each surrounding cell is linked to the cell of the LDD that it flows into. The topographic height of each LDD cell is subtracted from the topographic height of all linked cells, to obtain the Height Above Nearest Drainage (HAND) value for each cell. In the context of flood modelling, the inundation extent is then determined by selecting the surrounding cells with HAND values less than the known water depth in the stream (McGrath et al., 2018). A great advantage of the HAND model is that it does not only use the DEM like other types of conceptual modelling approaches (e.g. the planar or bathtub approach (McGrath et al., 2018)), but also derivate properties such as the slope and flow direction. As a result, the HAND model is capable of predicting inundation maps with high accuracy, and is now even applied in a web-based environment allowing users to edit the terrain and immediately see the effects of their actions on flood extents (Hu & Demir, 2021). Such tools offer potential benefits to decision makers when deciding on construction measures and to quickly study the effect of multiple flood scenarios on flood extents.

However, a disadvantage of the HAND model, and conceptual modelling approaches in general, is that only maximum inundation extents are predicted based on a total flood volume, giving no insight in the flood propagation and time series behavior of the water levels while this information is highly important to set up safe evacuation routes. Therefore, we are currently at a crossroad: do we invest more time and effort in the development and training of proper emulators, even though these need to be retrained after any changes in the DEM, or do we go back to the use of the conceptual modelling approaches by trying to improve these methods such that they will be able to predict flood time series? Another option is to combine both methods as they might complement each other.

6. CONCLUSIONS

During extreme flood events, dikes may fail, causing inundations in the hinterland. To reduce flood damage, proper early flood warning systems need to be developed such that the areas at risk can be evacuated on time. In this study, two emulators of the type NARX neural networks are developed for two potential dike failure locations in the Dutch Rhine river delta. These emulators were able to accurately predict if one of the potential dike failure locations failed based on an upstream discharge wave. Furthermore, if a dike section failed, the timing as well as the outflowing hydrograph were accurately predicted by the emulators.

Even though the simulation time of the emulators is extremely fast, the emulators need sufficient data for the training procedure. This training data is generally created with a detailed hydraulic model since not sufficient field measurements of flood events are available. The creation of this training data is extremely time consuming and the limiting factor in the development of accurate emulators. The need of a sufficiently large training data set, in combination with the fact that emulators need to be retrained in case of any changes in the DEM, makes the applicability of emulators as a real-time flood forecasting system questionable. Instead, a conceptual modelling approach, based on simplified hydraulic concepts, might be more applicable. These methods are also able to predict inundation maps accurately and fast. However, they are not able to provide flood propagation and time series behavior of water depths in the hinterland during a flood event. Therefore, the question which method is most appropriate to be used as a real-time flood forecasting system remains unsolved.

7. ACKNOWLEDGEMENTS

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