Water Resources Research

RESEARCH ARTICLE

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Special Section:
Advancing flood characterization, modeling, and communication

Key Points:

- Fast deep learning flood inundation models are developed to emulate a time-consuming two-dimensional hydrodynamic model for a flat floodplain
- One-dimensional (1D) convolutional models and a U-Net model are developed to simulate representative flood depths and to reconstruct the flood surface
- The combination of using 1D convolutional and U-Net models outperform an approach based on recurrent models and linear interpolation

Supporting Information:

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

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Deep Learning-Based Rapid Flood Inundation Modeling for Flat Floodplains With Complex Flow Paths

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Abstract Flood inundation emulation models based on deep neural networks have been developed to overcome the computational burden of two-dimensional (2D) hydrodynamic models. Challenges remain for flat and complex floodplains where many anabranches form during flood events. In this study, we propose a new approach to simulate the temporal and spatial variation of flood inundation for a floodplain with complex flow paths. A U-Net-based spatial reduction and reconstruction method (USRR) is used to find representative locations on the floodplain with complex flow paths. The water depths at these locations are simulated using one-dimensional convolutional neural network (1D-CNN) models, which are well-suited to handling multivariate timeseries inputs. The flood surface is then reconstructed using the USRR method and the simulated flood depths at the representative locations. The combined 1D-CNN and USRR method is compared with a previously developed approach based on the long short-term memory recurrent neural network (LSTM) models and a 2D linear interpolation-based SRR method. Compared to the LSTM model, the 1D-CNN model is not only more accurate, but also takes less time to develop. Although both surface reconstruction methods take <1 s to produce an inundation map for a specific point in time, the USRR method is more accurate than the SRR method, leading to an increase of 5.6% in the proportion of correctly detected inundation area. The combination of 1D-CNN and USRR can detect over 95% of the inundated area simulated using a 2D hydrodynamic model but is 98 times faster.

1. Introduction

Accurate and rapid flood inundation modeling is of great significance in engineering applications such as flood risk management and real-time forecasting. For decades, two-dimensional (2D) hydrodynamic models have been a popular method as they generally produce reliable simulation results (Horritt & Bates, 2002; Néelz & Pender, 2013). Despite the much-improved computing technologies and the increase of high-resolution observations, 2D models still incur an excessive computational burden and therefore they are not well suited to applications such as real-time operational flood forecasting and uncertainty analysis (Dottori et al., 2013; Gomez et al., 2019; Wu et al., 2020).

To improve modeling efficiency, a range of simplified inundation models have been developed, the majority of which are based on the conservation of mass of flood water (Bernini & Franchini, 2013; Lhomme et al., 2008; Teng et al., 2015; Zheng et al., 2018). These models estimate flood depth and extent by spreading the total volume of flood water over the modeling domain based on topography, and they are mostly applied for flood risk mapping at large scales. Due to the over-simplification of flood water dynamics in these models, they have difficulty in capturing the temporal dynamics and hydrodynamic controls of flood inundation behavior. Their applications are thus limited to estimating the maximum extent of flood inundation, and they are not suited to modeling flat regions where the flow dynamics have a large influence on the temporal and spatial evolution of floods (Bernini & Franchini, 2013; Teng et al., 2018).

As an alternative to these simplified models, data-driven emulation models have been developed using techniques that include traditional artificial neural networks, machine learning classification, as well as deep learning (DL) (Chang et al., 2010, 2014, 2018; Chu et al., 2019; Guo et al., 2021; Hu et al., 2019; Huang et al., 2021; Kabir et al., 2020; Kao et al., 2021; Löwe et al., 2021; Xie et al., 2020). These emulation models have been proven effective and computationally efficient when used to model the relationships between flood drivers and water depths/levels. However, most of these data-driven models have been developed to simulate flood conditions at each individual grid cells in the modeling domain. For example, for a modeling domain with 1 million grid cells, it would be necessary to develop 1 million emulation models. Such an approach leads to redundancy in computational effort as water levels in adjacent grid cells are correlated. Alternatively, a single model has been developed for all grid cells, and this approach is prone to overfitting due to the large size of the model and the limited availability of flood inundation data, which has significantly reduced the ability to accurately simulate future flood events (LeCun et al., 2015). In addition, although it has been found to work well in data-rich regions, the individual grid cell-based approach has been found to have reduced accuracy in data-scarce regions (Ben-Haim et al., 2019; Xie et al., 2020).

To overcome the above issues related to data-driven emulation methods, Zhou et al. (2021b) introduced an approach based on the combined use of long short-term memory recurrent neural network (LSTM) models and a 2D linear interpolation-based spatial reduction and reconstruction (SRR) method (Zhou et al., 2021a). The SRR method is used to first search for a subset of locations (small in number compared to the total number of grid cells in the model domain) which are representative of the spatial differences in inundation across the entire inundation surface. Then the LSTM models are used to handle the temporal dependency between timeseries inflow inputs and water level outputs. Finally, the SRR method is used to reconstruct the water surface based on the water level outputs simulated at the representative locations. In the case study presented by Zhou et al. (2021b), this SRR-LSTM approach represented the temporal evolution of inundation behavior across all 3 million grid cells of the modelling domain with only 125 LSTM models. While this approach considerably reduced the computational burden involved, it was found that the performance of the SRR method decreased when modelling dynamic behavior over flat floodplains comprised of multiple flow pathways and complex anabranches.

Given this difficulty, this paper aims to develop a robust flood inundation modelling approach that can emulate inundation behavior without the loss in accuracy exhibited by the SRR method when applied to flat complex floodplains. A framework including U-Net-based spatial reduction and reconstruction method (USRR) and one-dimensional convolutional neural network (1D-CNN) models is proposed. The U-Net architecture was originally developed by Ronneberger et al. (2015) for biomedical image segmentation, and it has been found to effectively capture the spatial correlation of rainfall-triggered flood inundation surfaces (Guo et al., 2021; Löwe et al., 2021). Thus, rather than directly interpolating between representative water levels with the SRR method, a U-Net neural network is used to include topographic data as inputs to build the relationship between representative water depths and the flood inundation surface over the floodplain. The 1D-CNN models are then developed to simulate water depths at representative locations. 1D-CNN models have been used for time series modelling in past research (Kabir et al., 2020; Kratzert et al., 2018; LeCun & Bengio, 1995; Sahoo et al., 2019; Van et al., 2020). These models have some advantages compared to the LSTM models, including that they are highly parallelizable, as well as the stable gradients and the low memory requirement during their training process (Bai et al., 2018). In this study, the performance of the coupled USRR-1D-CNN approach for flood inundation modelling is evaluated using a real-world, flat, and complex floodplain in northern Victoria, Australia.

2. Methodology

The overview of the framework for modeling flood inundation across complex floodplains with complex flow paths is illustrated in Figure 1a. The framework includes the USRR method and the 1D-CNN models for water depth simulation, where:

1. The USRR method is developed to
   a) select representative locations in the modeling domain, and
   b) reconstruct the flood inundation surface using water depths at selected representative locations;
3. 1D-CNN models are developed to simulate the water depths at representative locations selected using the USRR method.

Details of each method are introduced below.

2.1. U-Net-Based Spatial Reduction and Reconstruction

The USRR method aims to find representative locations on flat floodplains where the water depth information can be used to reconstruct the entire flood inundation surface. It consists of two modules: (a) the representative

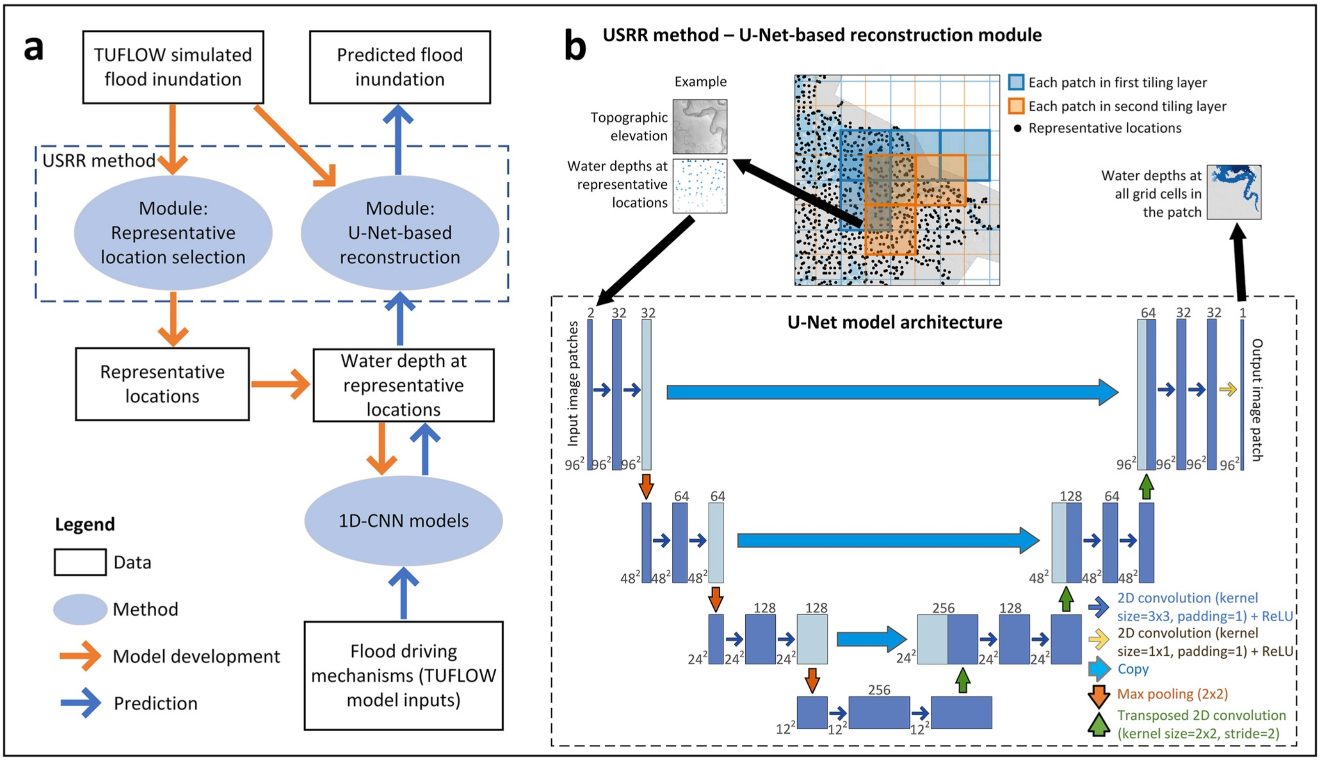

Figure 1. Overview of (a) the U-Net-based spatial reduction and reconstruction-one-dimensional convolutional neural network (USRR-1D-CNN) approach, (b) the U-Net-based reconstruction module of USRR method and the architecture of the U-Net model.

location selection module and (b) the U-Net-based reconstruction module. Details of each module is introduced below.

2.1.1. Representative Location Selection Module

The representative location selection module is developed to select the representative locations on the floodplain where the water depth information can be used to estimate the inundation behavior over the entire modeling domain. This module aims to capture the complex flood flow dynamics on flat floodplains using only the depth information at a smaller number of locations.

The process starts with tiling the potential inundation domain into regular rectangular grids, and then one representative location is determined for each rectangular grid. In each grid, the location with the lowest elevation, where is most likely to be inundated during floods, is selected to maximize flood data available for model development. Selecting the size of the grids (and hence the number of representative locations) involves a trade-off between computational efficiency and accuracy, and this trade-off needs to be evaluated on a case-by-case basis. The larger the grid size, the fewer representative locations are selected, and the more efficient is the approach; however, selection of a small number of representative locations reduces the ability of the overall approach to accurately capture the dynamics of flood behavior in complex situations. In general terms, the size of grids can be larger for steep floodplains with simple flow paths and smaller for flat floodplains with complex flow paths. A suitable size for grids can be determined based on expert judgment or simple accuracy tests such as linearly interpolating between locations. After selection, the water depth information at the required locations is retrieved from the 2D hydrodynamic model results for the development of DL models for water depth simulation.

2.1.2. U-Net-Based Reconstruction Module

The U-Net-based reconstruction module in the USRR method is developed for reconstructing the inundation surfaces based on simulated water depth information at the selected representative locations. The key part of this module is the development of the U-Net model. The inputs taken by the U-Net model are the topographic elevations and the water depths at representative locations over the area of a single patch (where each patch is a

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square area covering a portion of the modeling domain as demonstrated with blue or orange boxes in Figure 1b). The output of the model is an image of the same size as the inputs, with the reconstructed water depth in each grid cell. Two key modifications have been made to the architecture of the U-Net model developed by Ronneberger et al. (2015) for the purpose of flood surface reconstruction: (a) the size of the input images as well as the number of neural network layers in the model are reduced from the original design to reduce the model size to avoid overfitting; and (b) additional grid cells are added to each side of the image during the 2D convolutional calculations (also known as "padding" in 2D convolutional layers) to ensure consistent sizes between the input and output images. The modified architecture of the U-Net model is presented in Figure 1b.

Two layers of patches are used to apply the U-Net model to reconstruct an inundation surface across the entire domain. The first layer is created by tiling the modeling area into sub-grids of the size of the U-Net inputs. Then the patches in this layer are shifted a pre-defined distance (less than the dimension of a single patch) to create the second layer of patches. In both layers, only those patches that cover at least one representative location are selected. During the training process, information on topographic elevations and water depths at representative locations, and the full water depths at all grid cells in each patch are extracted from the inundation database simulated using the 2D hydrodynamic model. The data are then used for U-Net model training. During the prediction process, the images containing reconstructed water depths produced using the U-Net model are merged to form the final inundation surface covering the entire modeling domain. In regions where the two layers overlap, the average depth is used.

2.2. 1D-CNN for Water Depth Simulation

1D-CNN models are developed to simulate the water depths at representative locations based on flood drivers related to inflows and boundary conditions. The architecture of the 1D-CNN model consists of an input layer, two 1D convolutional layers, two max-pooling layers, a feed-forward layer, and an output layer, as shown in Figure 2.

The input layer is the first layer that takes multivariate time series inputs, such as inflows at various locations in the modeling domain. The second layer is a 1D convolutional layer, which performs 1D convolution along the temporal dimension of each input variable. The input or output sequence for the 1D convolutional layer is referred to as a "channel." Hence, the number of input channels in this second layer equals the number of input variables, while the number of output channels is one of the hyperparameters to be determined during the calibration. A max-pooling layer is used after the second layer to reduce the size of the data vector. The hyperbolic tangent function (tanh) is used as the activation function for the output neurons in this layer. Similar to the second and third layers, the fourth layer also performs 1D convolutional operation and is followed by a max-pooling layer. The number of input channels in the fourth layer equals the number of output channels of the previous layer, where the number of output channels is another hyperparameter that needs to be determined. The activation function used in the fifth layer is the leaky rectified linear unit (Leaky-ReLU), which is found to improve the stability of the calibration process (Maas et al., 2013).

Each element in the output of the fifth layer is treated as one neuron, which is passed to the feed-forward layer activated with the Leaky-ReLU function. The number of neurons in this layer is one of the hyperparameters. The output layer is also a feed-forward layer which takes a weighted sum of the received data from the previous layer and converts them into water depths, which are the final outputs. Each neuron in the output layer provides estimates of water depth at one representative location at a specific time. To produce time series outputs, the input time series to the 1D-CNN model are shifted forward by one timestep at a time.

To reduce computational burden, each 1D-CNN model is developed to simulate water depths at a group of locations. The groups are formed using the k-mean method (MacQueen, 1967) based on the spatial coordinates of the representative locations selected by the USRR method. To prevent overfitting, the sizes of the models are constrained by having a small number of locations in each group, which is in turn determined by the total number of groups (the K value) used in the k-mean method. In other words, the optimal total number of groups is determined based on the complexity of the water depth information and the availability of training data.

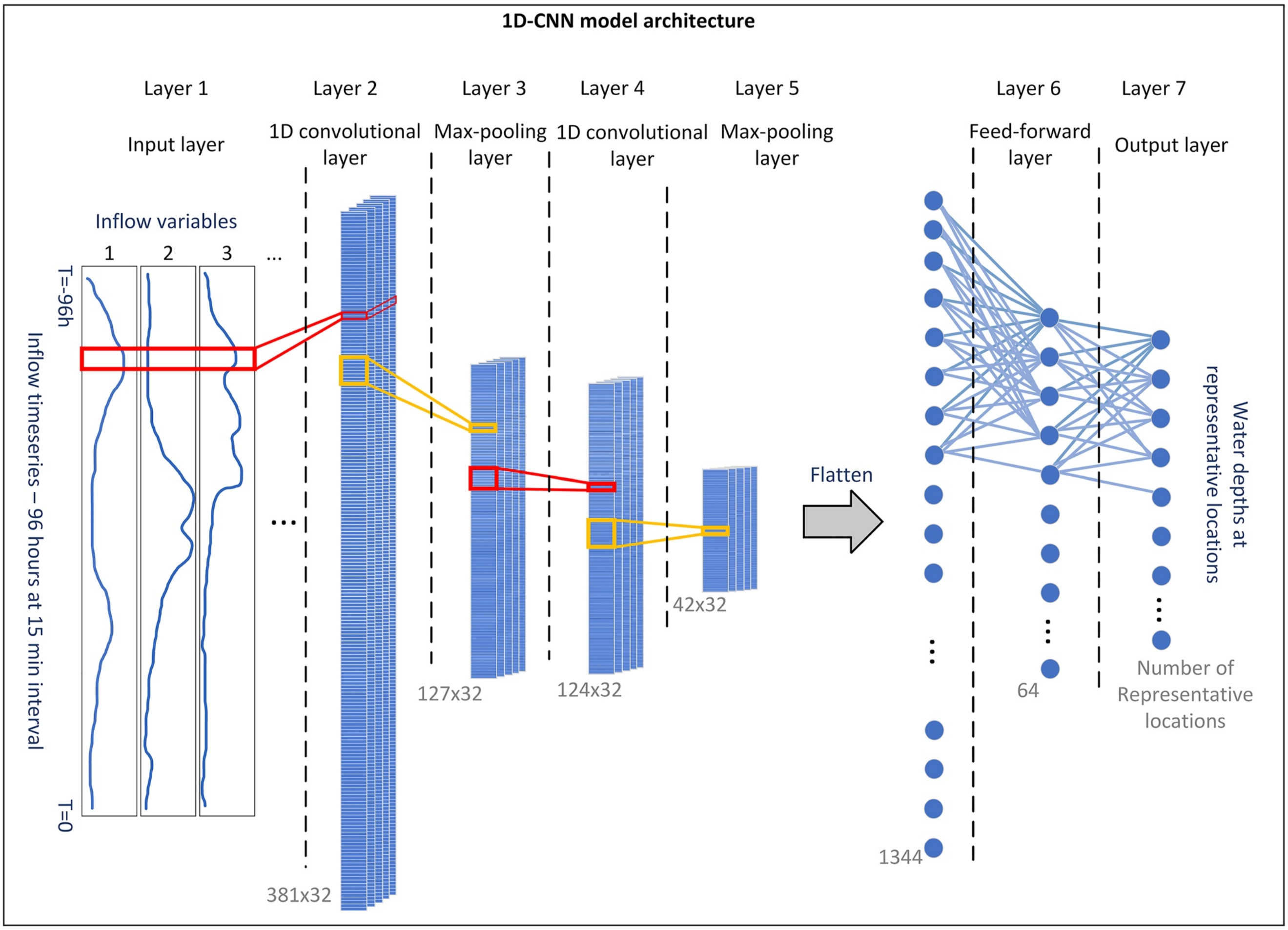

Figure 2. Architecture of one-dimensional convolutional neural network (1D-CNN) model.

3. Case Study

3.1. Study Area and Hydrodynamic Model

The USRR-1D-CNN approach for flood inundation simulation is evaluated using the King River-Ovens River system in Victoria, Australia. The location and extent of the model domain are shown in Figure 3a. The length of the King River reach before it joins the Ovens River is approximately 68 km, and the length of the Ovens River reach to the downstream boundary is about 25 km. The study area has a flat floodplain which exhibits complex flow behavior that changes in response to different river levels during flooding.

The USRR-1D-CNN approach is used to emulate a TUFLOW HPC 2D hydrodynamic model developed for the system (Collecutt & Syme, 2017; Huxley & Syme, 2016). The original model domain of the TUFLOW model contains 3,911,243 10 m-by-10 m active grid cells and covers an area of around 391 km^2, while the USRR-1D-CNN approach is applied to the area within the maximum inundation extent of flood events used for development. The refined model domain contains 1,830,758 grid cells. The model has in total 33 inputs, including two main inflows and 31 concurrent tributary inflows, as shown in Figure 3a. The main inflows are released from the Lake William Hovell into King River, and also from the Ovens River catchment. Uniform flow conditions are assumed at the downstream boundary where the slope of the water surface is the same as the slope of the riverbed. More details of the TUFLOW model configurations can be found in Section A in Supporting Information S1.

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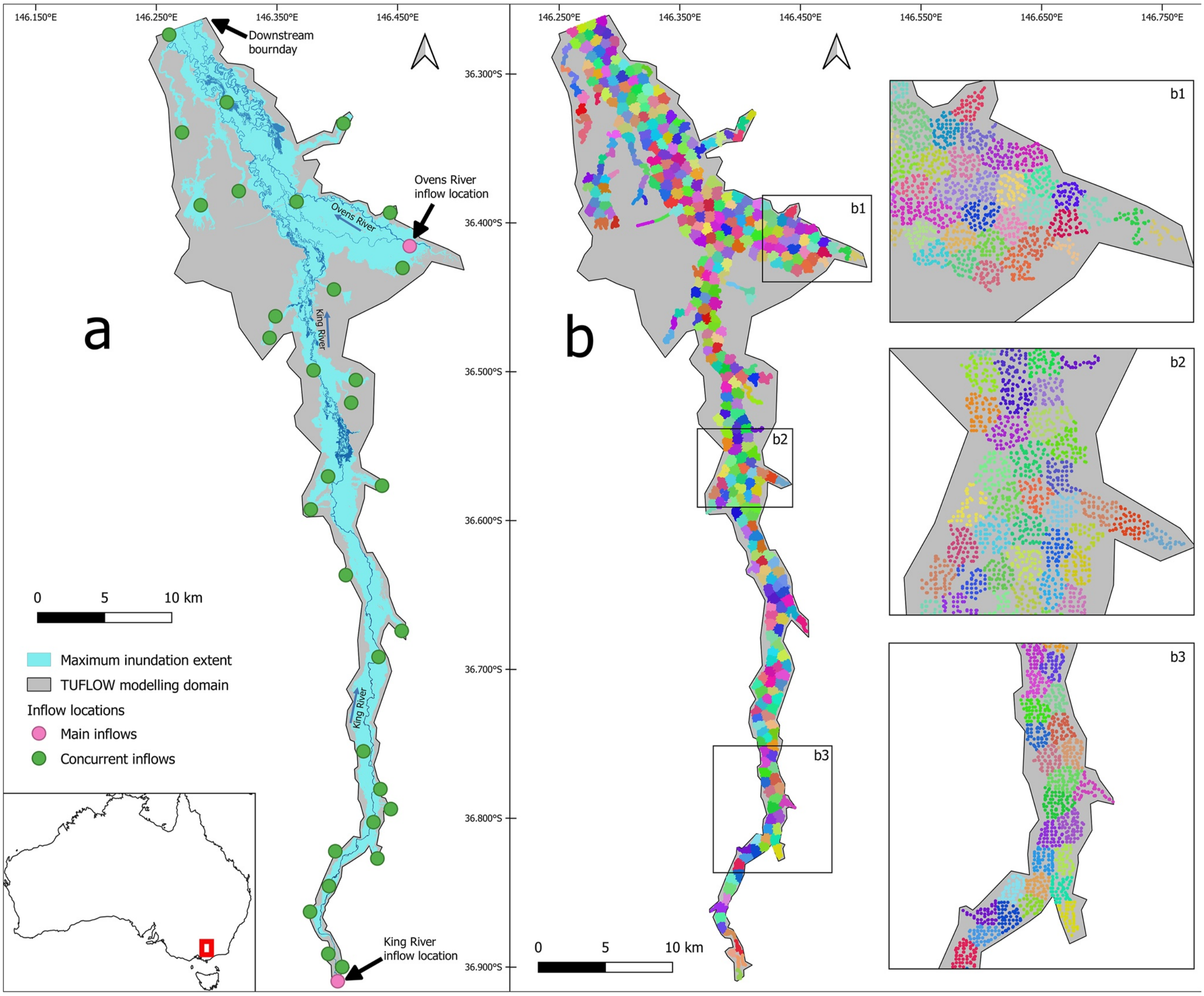

Figure 3. (a) Model domain and locations of inflows of the King River-Ovens River system. (b) Representative locations (points) for the King River-Ovens River system selected using the U-Net-based spatial reduction and reconstruction-one-dimensional convolutional neural network (USRR-1D-CNN) approach, where different colors in points indicate the grouping of representative locations for the development of 1D-CNN models.

3.2. Flood Event Data Sets

The data set used in this study contains 18 historical flood events and 36 design flood events. The average recurrence intervals (ARIs) of these events range from 2 to 500 years. A summary of all 54 events can be found in Section B in Supporting Information S1. The river discharge data is sourced from both Hydrology and Risk Consulting and Water Data Online (www.bom.gov.au/waterdata) of Australian Bureau of Meteorology. For all events, flood inundation data were generated using the TUFLOW model based on inflows at a 15-min time-step. All input variables, as well as the inundation data, are included for the development of the USRR-1D-CNN approach.

3.3. Model Development Process

3.3.1. Identifying Representative Locations

The representative location selection module of the USRR method described in Section 2.1.1 is used to find the representative locations in the modeling domain. The potential inundation domain is divided into regular rectangular windows of size 100 m by 100 m, that is, each window is based on a ten-by-10 set of grid cells from the

TUFLOW model. A single representative location is selected from each window, resulting in a total of 21,113 representative locations. The selected representative locations are shown in Figure 3b. The water depth information is retrieved from the flood depth results simulated using the TUFLOW model.

3.3.2. Data Splitting

The calibration of the U-Net and 1D-CNN models includes training and testing. Forty flood events are used to train the U-Net and 1D-CNN models, and 10 flood events are used as testing data for choosing training hyperparameters and to avoid over-fitting. After the calibration of the DL models, the remaining four historical flood events (i.e., events 1–4 in Section B in Supporting Information S1, hereafter referred to as validation events 1, 2, 3, and 4, respectively) are used for the validation of the USRR-1D-CNN approach in flood inundation modeling. The detailed information of these events can be found in Section B in Supporting Information S1.

3.3.3. Training of U-Net Model for Flood Surface Reconstruction

The U-Net model in the USRR method is trained to provide flood surface estimates based on the water depth information at representative locations as well as the topographic elevation in the target area. The U-Net model is developed to take input images of 96-by-96 grid cells. The inputs include one digital elevation model image and one image containing water depths at corresponding grid cells of representative locations. The output of the U-Net model is an image of 96-by-96 grid cells containing predicted water depths at all cells. Detailed model dimensions for each layer can be found in Figure 1b.

The training data are prepared using an inundation map which is extracted from the TUFLOW model results at a 5-hr interval and tiled into images of 96-by-96 grid cells in size. We found during experiment that the model tends to underestimate water depths due to the existence of many dry images (i.e., images of dry 96-by-96 grid cells) in the training data. Therefore, in each training set, the images are resampled to reduce the number of dry images to avoid biasing the training process. Following the above process, the sample size for training and testing are 751,551 and 191,413, extracted from the 40 training events and 10 testing events, respectively.

The other hyperparameters for training the U-Net model are optimized including learning rate (0.001) and maximum epoch number (30) coupled with early stopping criteria. The mean squared error (MSE) loss function and the Adam optimizer (Kingma & Ba, 2014) is used for training. The trained U-Net model is used to reconstruct the depths in each patch. The output images are then merged to provide the inundation surface reconstruction of the entire modeling domain as introduced in Section 2.1.2. The U-Net-based reconstruction module is automated in a Python program, which is developed with the support of the Pytorch package (Paszke et al., 2019) for Graphics Processing Units (GPUs) acceleration.

3.3.4. Training of 1D-CNN Models for Water Depth Simulation

The 1D-CNN models are developed using the simulated water depth data at representative locations using the TUFLOW model for the 40 training flood events and the 10 testing flood events. The 21,113 representative locations are divided into 423 groups using the k-mean method introduced in Section 2.2, and the resulting groups are illustrated using different colors in Figure 3b. A total of 423 1D-CNN models are developed for the 423 groups and each is used to estimate water depths at multiple locations within each group. The number of representative locations in each group, which is also the number of outputs in each 1D-CNN model, ranges from 12 to 78. The sample size for training and testing are 24,000 and 6,000, respectively.

The 1D-CNN model has 33 neurons in the input layer, corresponding to the 33 inflow input variables. Each variable in the input layer is a vector that contains the time series of inflow at one location. For simulating the current water depths, the inflow time series of the past 96 hr are used. The 1D convolutional layers in the 1D-CNN are optimized to have 32 output "channels," with the size of the convolution kernels being four. The kernel size of the max-pooling operations is three, and the feed-forward layer has 64 neurons, while the number of neurons in the output layer is determined by the number of representative locations in the current group. Other hyperparameters for training are optimized using the testing data, including batch size (50), learning rate (0.001), and maximum epoch number (40) coupled with early stopping criteria. The final epoch number for each model is determined using early stopping and summarized in Zhou et al. (2022). The MSE loss function and the Adam optimizer (Kingma & Ba, 2014) are used for training. Detailed model dimensions for each layer can be found in Figure 1c.

3.3.5. Model Validation

Model validation is conducted separately for the USRR method, the 1D-CNN models, and the overall USRR-1D-CNN approach. The evaluation metrics used for each part of the validations are introduced below.

The USRR method is validated by evaluating the reconstruction accuracy using as inputs the depth information at representative locations simulated using the TUFLOW model to avoid introducing errors from the simulated water depths using 1D-CNN models. Three commonly used metrics are used, including the root mean squared error (RMSE), the probability of detection (POD), and the rate of false alarm (RFA) (Chu et al., 2019; Xie et al., 2020; Zhou et al., 2021b). The POD represents the proportion of inundated area detected using the reconstruction method, while the RFA represents the proportion of reconstructed inundation area where is dry in the TUFLOW simulated results. The depth information at representative locations simulated using the TUFLOW model is used as inputs for reconstructing inundation maps to avoid introducing errors from the simulated water depths using 1D-CNN models. A threshold water depth of 0.05 m is used to differentiate between wet and dry grid cells in the reconstructed inundation surface. The equations used to calculate the three performance metrics are provided below.

$$\mathrm{RMSE} = \sqrt{\frac{1}{T \times N} \sum_{n=1}^{N} \sum_{t=1}^{T} \left(D_n^t - W_n^t\right)^2} \tag{1}$$

$$\mathrm{POD} = \mathrm{Area}_{\mathrm{detected}} / (\mathrm{Area}_{\mathrm{detected}} + \mathrm{Area}_{\mathrm{missed}}) \times 100\% \tag{2}$$

$$\mathrm{RFA} = \mathrm{Area}_{\mathrm{false\ alarm}} / (\mathrm{Area}_{\mathrm{detected}} + \mathrm{Area}_{\mathrm{false\ alarm}}) \times 100\% \tag{3}$$

where T is the number of time steps, N is the number of grid cells in the modeling domain, D_n^t represents the water depth estimated using the USRR method in the nth grid cell at the tth time step, W_n^t represents the water depth simulated using the TUFLOW model in the nth grid cell at the tth time step, $\mathrm{Area}_{\mathrm{detected}}$ is the area of inundation that presents in inundation extents estimated using both the USRR method and the TUFLOW model, $\mathrm{Area}_{\mathrm{missed}}$ is the area of inundation that presents in the results of the TUFLOW model but is not detected using the USRR method, and $\mathrm{Area}_{\mathrm{false\ alarm}}$ is the area of inundation estimated using the USRR method but which is dry in the TUFLOW model simulation results.

The 1D-CNN models are validated in terms of the predictive performance for the four validation flood events. The performance is evaluated using RMSE of simulated water depth time series at all representative locations for each event.

The validation of the overall USRR-1D-CNN approach is carried out using a range of metrics for the flood depths across the modeling domain, the maximum inundation extent, and the temporal flood inundation evolution. The 0.05 m threshold water depth used for the USRR method validation is also adopted here. For the flood depths across the modeling domain, the approach is evaluated using the spatial RMSE estimated for the water depth at each grid cell. The performance metrics POD and RFA are used to evaluate the maximum inundation extent. The temporal flood inundation evolution is evaluated in terms of the total inundation area, POD, and RFA of the inundation extent at each timestep simulated using the USRR-1D-CNN approach.

For the evaluation of the USRR-1D-CNN approach, its performance is compared to the SRR-LSTM approach introduced in Zhou et al. (2021b). A brief introduction of the SRR-LSTM approach can be found in the Introduction section, and details of the development process of the SRR-LSTM approach for this case study can be found in Section C in Supporting Information S1.

4. Results and Discussion

The results below are presented in four sections that deal separately with (a) the validation of the USRR method; (b) the validation of the 1D-CNN models; (c) the validation of the overall USRR-1D-CNN approach for flood inundation modeling; and (d) the evaluation of the computational efficiency of the USRR-1D-CNN approach.

Table 1
Water Depth Root Mean Squared Error (RMSE), Average Probability of Detection (POD) and Average Rate of False Alarm (RFA) of Reconstructed Inundation Maps, and Computational Time Using U-Net-Based Spatial Reduction and Reconstruction (USRR) Method and Spatial Reduction and Reconstruction (SRR) Method for Validation Events, in Comparison With the TUFLOW Simulated Inundation

Method name	Water depth RMSE (m)	Average POD (%)	Average RFA (%)
USRR	0.034	97.6	5.4
SRR	0.128	92.0	8.0

4.1. Reconstruction Accuracy of the USRR Method

The reconstruction accuracy of the USRR method is evaluated for the four validation events with reference to the flood inundation results obtained from the TUFLOW model. To avoid the impacts of errors in water depths simulated using 1D-CNN models, the depths at representative locations from the TUFLOW model results are used as inputs to the USRR reconstruction module to reconstruct the inundation maps for the evaluation of the USRR method. The water depth RMSE, POD and RFA for reconstructed inundation maps are presented in Table 1.

The reconstructed inundation surface using the USRR captures reasonably well the depth and extent of the inundation simulated using the TUFLOW model. The reconstructed inundation extents using the USRR method for all four validation events correctly detect on average 97.6% of the inundated area simulated using the TUFLOW model, where on average 5.4% of the model domain is falsely estimated to be inundated. The overall RMSE of reconstructed depths using the USRR method is 0.034 m.

Compared to the SRR method developed as part of the SRR-LSTM approach (Zhou et al., 2021b), the USRR method achieves better accuracy in terms of both flood inundation depth and extent. Compared to the SRR method, the reconstructed inundation extent using the USRR method detects on average 5.6% more of the inundated area, and has 2.6% less falsely estimated inundation area. The RMSE of reconstructed depths reaches 0.128 m using the SRR method, which is 0.094 m higher than that obtained using the USRR method.

4.2. Predictive Performance of 1D-CNN Models

The predictive performance of the 423 1D-CNN models is first evaluated against the TUFLOW model results using the RMSE of the modeled depths at the 21,113 representative locations. The RMSE of the water depths for the four validation events are presented in Table 2. The 1D-CNN models perform well in simulating the water depths at representative locations, with the overall RMSE being 0.087 m for the four validation events. The predictive performance of 1D-CNN models tends to be worse for smaller events except event 3. The RMSE is the smallest for validation event 3 which is 0.055 m and reaches the largest at 0.107 m for validation event 4 which is the smallest flood event.

When compared with the LSTM models developed as part of the SRR-LSTM approach, the 1D-CNN models perform slightly better in terms of the overall RMSE for validation events, as presented in Table 2. The overall water depth RMSE simulated using the LSTM model is 0.099 m which is 0.012 m higher than that using the 1D-CNN models. For different flood events, the RMSEs of the depths simulated using the 1D-CNN models are also generally lower than that using LSTM models. The largest difference is for the largest flood event (validation event 1), which reaches 0.023 m, while the differences for other events are around 0.01 m.

Table 2
Water Depth Root Mean Squared Error (RMSE) for One-Dimensional Convolutional Neural Network (1D-CNN) Models and Long Short-Term Memory (LSTM) Models for the Four Validation Events Compared to the TUFLOW Model Results

		Water depth RMSE (m)	
Validation event no.	ARI[a] (years)	1D-CNN	LSTM
1	53	0.079	0.102
2	51	0.094	0.105
3	16	0.055	0.067
4	7	0.107	0.112
Overall		0.087	0.099

[a]Average recurrence interval estimated based on historical discharge of the Ovens River.

4.3. Flood Inundation Modeling Performance

4.3.1. Flood Inundation Depth

The flood inundation depths predicted using the USRR-1D-CNN approach are first compared in each grid cell with the depths simulated using the TUFLOW model for the four validation events. Results in Figure 4 show the cumulative percentage of grid cells where the RMSE is below different values for the simulated water depths. The spatial RMSE for validation event 1 are shown in Figure 5a, while the figures for other validation events can be found in Section D in Supporting Information S1.

The USRR-1D-CNN approach performs well in simulating the flood inundation depths, with an overall RMSE of 0.053 m. With reference to Figure 4, there are on average 95% of grid cells in the modeling domain with an RMSE

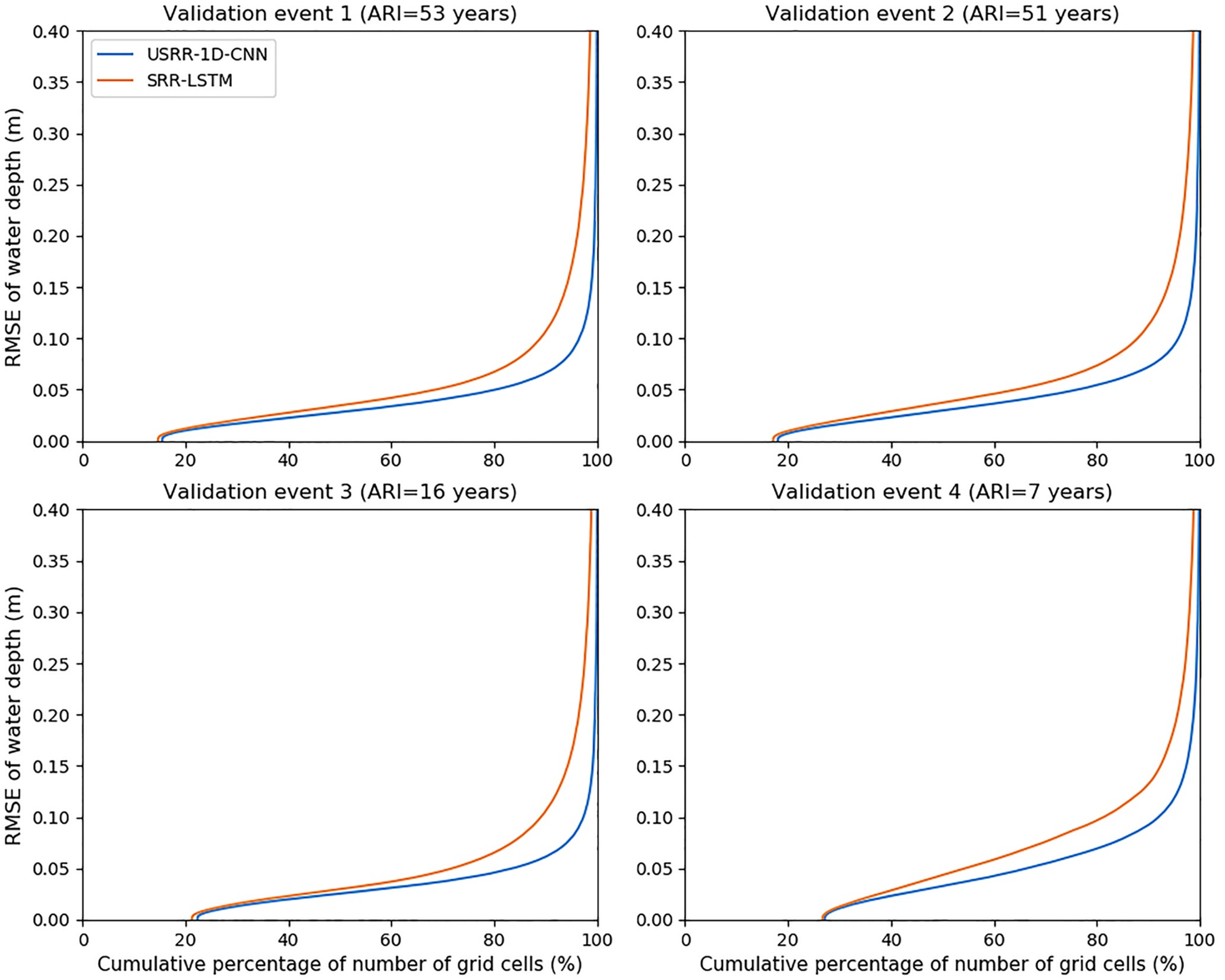

Figure 4. Cumulative percentage of number of grid cells with root mean squared error (RMSE) below different values for the water depths simulated using U-Net-based spatial reduction and reconstruction-one-dimensional convolutional neural network (USRR-1D-CNN) and spatial reduction and reconstruction-long short-term memory (SRR-LSTM) against TUFLOW results.

below 0.09 m. This indicates that using the USRR-1D-CNN approach to simulate the flood inundation depths leads to reasonably small errors for 95% of the modeling area when compared to the results obtained using the TUFLOW model. The RMSE of water depths using the USRR-1D-CNN approach for grid cells near the downstream boundary tends to be slightly higher than other regions, but is generally below 0.1 m as shown in Figure 5a. Additionally, the median relative RMSE is estimated to be 14.6% for the entire domain, and is 6.7% for area with average flood depth above 0.36 m. In other words, the USRR-1D-CNN approach performs reasonably well for both data-rich region and data-scarce region in terms of RMSE.

Compared to the SRR-LSTM approach, the USRR-1D-CNN approach performs generally better with the RMSE for the entire domain being 0.08 m lower. As shown in Figure 4, when the SRR-LSTM approach is used, only 86% of the modeling area (9% less than USRR-1D-CNN) has an RMSE below 0.09 m. Spatially, the RMSE of water depths simulated using the SRR-LSTM approach tends to be larger than that obtained using the USRR-1D-CNN approach in areas near the main rivers, as shown in Figures 5a and Figure 5b. The median relative RMSE for the domain area using the SRR-LSTM approach is also larger than that using the USRR-1D-CNN approach, reaching 19.1% for the entire domain and 7.9% for area with average flood depth above 0.36 m.

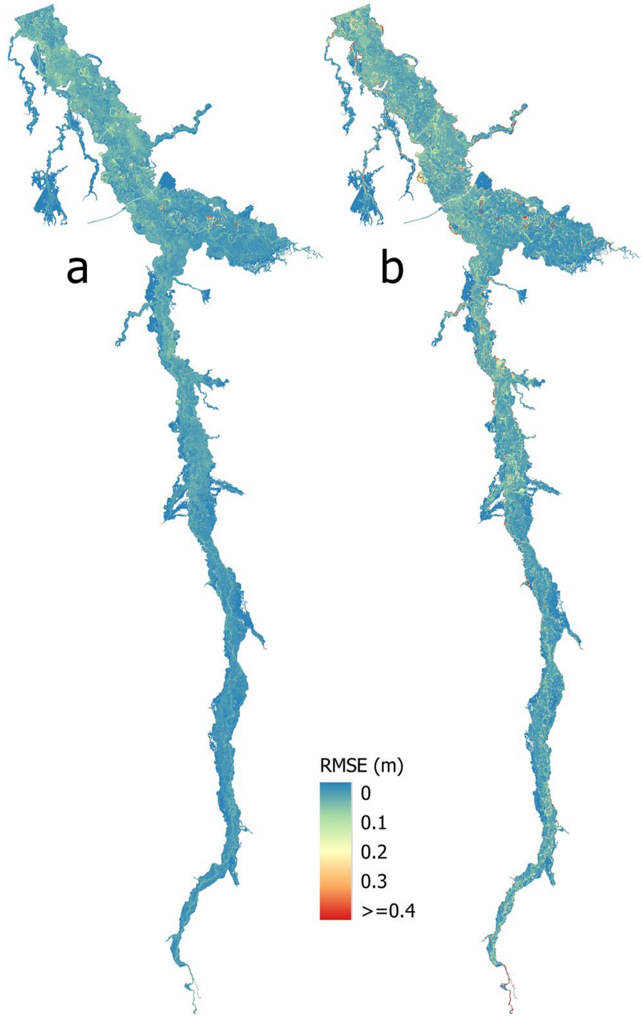

Figure 5. Root mean squared error (RMSE) of simulated flood inundation depth in each grid cell for validation event 1, in comparison with the TUFLOW model results. (a) RMSE using U-Net-based spatial reduction and reconstruction-one-dimensional convolutional neural network, (b) RMSE using spatial reduction and reconstruction-long short-term memory.

Table 3
Probability of Detection (POD) and Rate of False Alarm (RFA) for the Maximum Flood Inundation Extent Modeled Using U-Net-Based Spatial Reduction and Reconstruction-One-Dimensional Convolutional Neural Network (USRR-1D-CNN) and Spatial Reduction and Reconstruction-Long Short-Term Memory (SRR-LSTM) for Each Validation Event, in Comparison With the TUFLOW Model Results

	USRR-1D-CNN		SRR-LSTM	
Validation event no.	RFA (%)	POD (%)	RFA (%)	POD (%)
1	1.3	98.6	2.3	96.8
2	1.8	98.6	2.9	96.7
3	2.1	98.5	3.6	96.0
4	3.8	98.0	4.5	94.7

4.3.2. Maximum Flood Inundation Extent

The maximum flood inundation extents generated using the USRR-1D-CNN approach are evaluated for the four validation events. Table 3 summarizes the RFA and the POD of the simulated maximum flood inundation extents using the USRR-1D-CNN approach. The spatial comparison of the maximum inundation extents simulated using the USRR-1D-CNN approach for validation event 1 is shown in Figure 6a.

The USRR-1D-CNN approach detects over 98% of the maximum flood inundation extent determined using the TUFLOW model for all four validation events, with the RFAs being between 1.3% and 3.8%. This approach achieves higher accuracy for larger flood events, with the POD being 0.6% higher for event 1 than that for event 4, and the RFA being 2.5% lower. Figure 6a indicates that the spatial maximum inundation extent generated using the USRR-1D-CNN approach matches well with that simulated using the TUFLOW model.

In comparison with the SRR-LSTM approach, the USRR-1D-CNN approach detects on average 2.4% more inundated area at the maximum inundation extents and has the average 1% less falsely inundated area. Figure 6b shows the maximum inundation extent simulated using the SRR-LSTM approach, where the overestimation of maximum inundation extent can be found at locations fat into the floodplain (Figure 6b2). The results also show that the extent generated by SRR-LSTM has more missed inundation area in regions with relatively flat topology. Similar results can be found for the other three validation events, which are included in Section E in Supporting Information S1. Therefore, the USRR-1D-CNN approach is more suitable for modeling the maximum flood inundation extent on flat floodplains.

4.3.3. Temporal Evolution of Flood Inundation

The flood inundation evolution simulated using the USRR-1D-CNN approach is investigated by evaluating the flood inundation extent at every time step. Figure 7 shows three metrics used to evaluate the inundation extent estimates of the USRR-1D-CNN approach, including the changes of the total inundation area over time, the temporal POD, and the temporal RFA. The two main discharge inputs on King River and Ovens River for the four validation events are plotted on the top of the figure to show the evolution of the flood events.

The increase of inundation area in the modeling domain is well captured using the USRR-1D-CNN approach, while the timing of reaching the maximum inundation area is estimated to be only about half an hour earlier than that simulated using the TUFLOW model (i.e., two timesteps in the outputs). When accounting for the spatial accuracy of the simulated flood extents, the USRR-1D-CNN approach detects over 93% of the inundation area simulated using the TUFLOW model. The falsely predicted inundation area using this approach is generally below 10%. The USRR-1D-CNN approach performs better for flooding periods when the total inundation area increases with higher inflows. The PODs for flooding periods reach 98% and the RFAs drop for 5%.

Compared to the results obtained using the SRR-LSTM approach, the change of flood inundation extents simulated using the USRR-1D-CNN approach better matches the results of the TUFLOW model. Generally, the USRR-1D-CNN approach correctly detects 5% more inundation area with only 5% of the inundated area falsely inundated compared to the SRR-LSTM

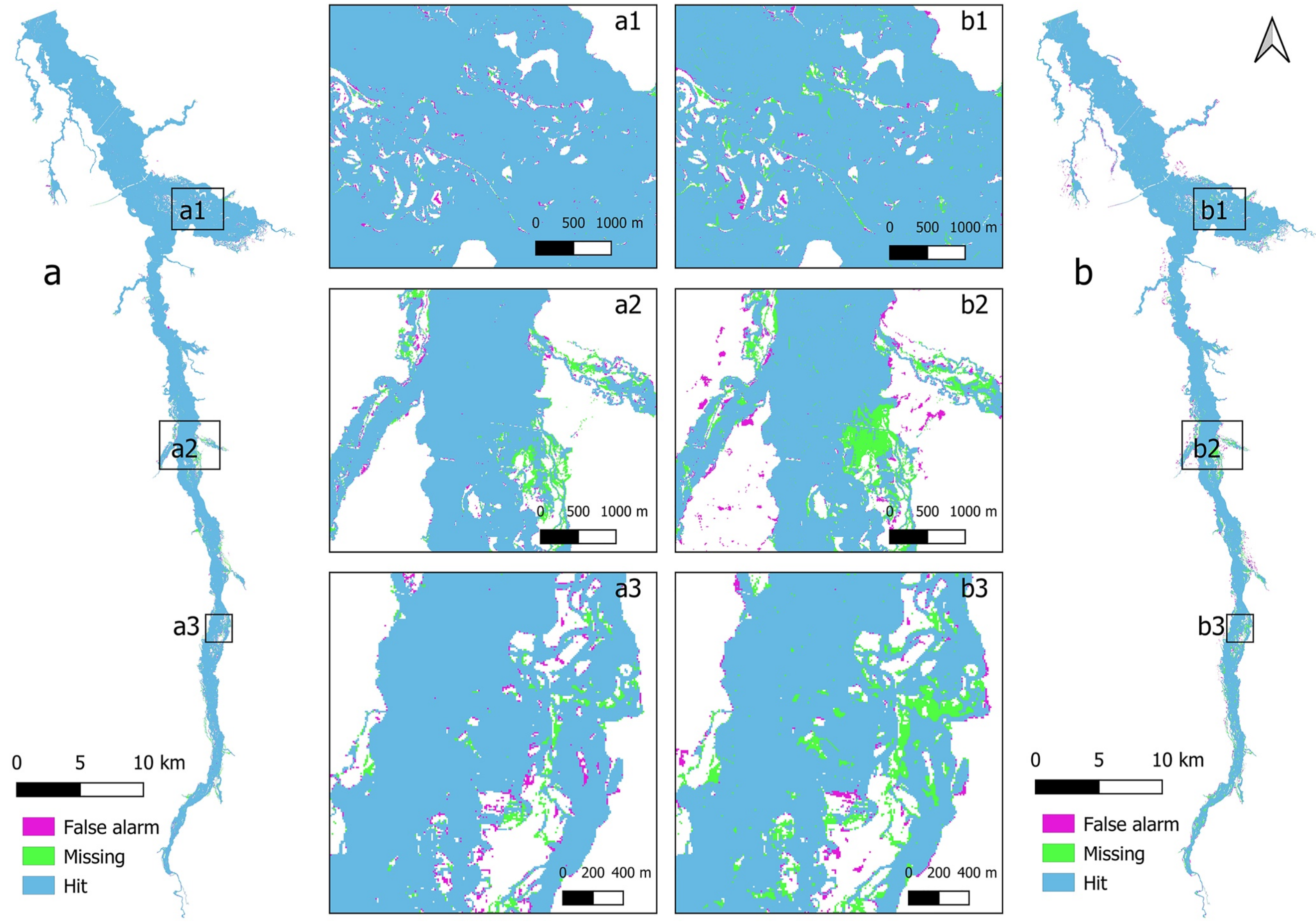

Figure 6. Comparison of the maximum inundation extents for validation event 1 simulated using (a) U-Net-based spatial reduction and reconstruction-one-dimensional convolutional neural network, and (b) spatial reduction and reconstruction-long short-term memory, with the TUFLOW model.

approach. The SRR-LSTM approach performs significantly worse than the new approach during low-inflow periods when the RFA reaches over 35%. Generally, the USRR-1D-CNN approach outperforms the SRR-LSTM approach by detecting more inundation area and making less false alarms.

Compared to simplified conceptual flood inundation models (Teng et al., 2017), the major advantage of the USRR-1D-CNN approach is that it provides temporal estimates of flood inundation with a reasonable level of accuracy instead of only the maximum inundation extent of the event. The 1D-CNN models have been proven to provide efficient handling of timeseries discharge inflows and providing estimates of water depths during flood events. In addition, compared to other surrogate models (Chu et al., 2019; Xie et al., 2020; Zhou et al., 2021b), the accuracy of reconstructed flood inundation surface is significantly improved with the USRR method, when the U-Net model is developed to capture the spatial correlation of water depths.

4.4. Computational Efficiency

The computational efficiency is evaluated considering the required training time for model development as well as the required computational time for flood event simulations. The comparison of computational efficiency between the USRR-1D-CNN approach, the SRR-LSTM approach, and the TUFLOW model is provided in Table 4. The speed tests are carried out on a computer with the CPU of Intel(R) Core (TM) i7-8700K @ 3.70ghz with 6 Cores and 32 GB RAM, and the GPUs of NVIDIA Quadro P5000 with dedicated memory of 16 GB. The TUFLOW model is run with GPU acceleration. The USRR-1D-CNN approach is programmed in Python and is also accelerated using the GPU with the support of the Pytorch package (Paszke et al., 2019). It should be noted that the modeling domain of the USRR-1D-CNN approach is defined using the maximum inundation extent of

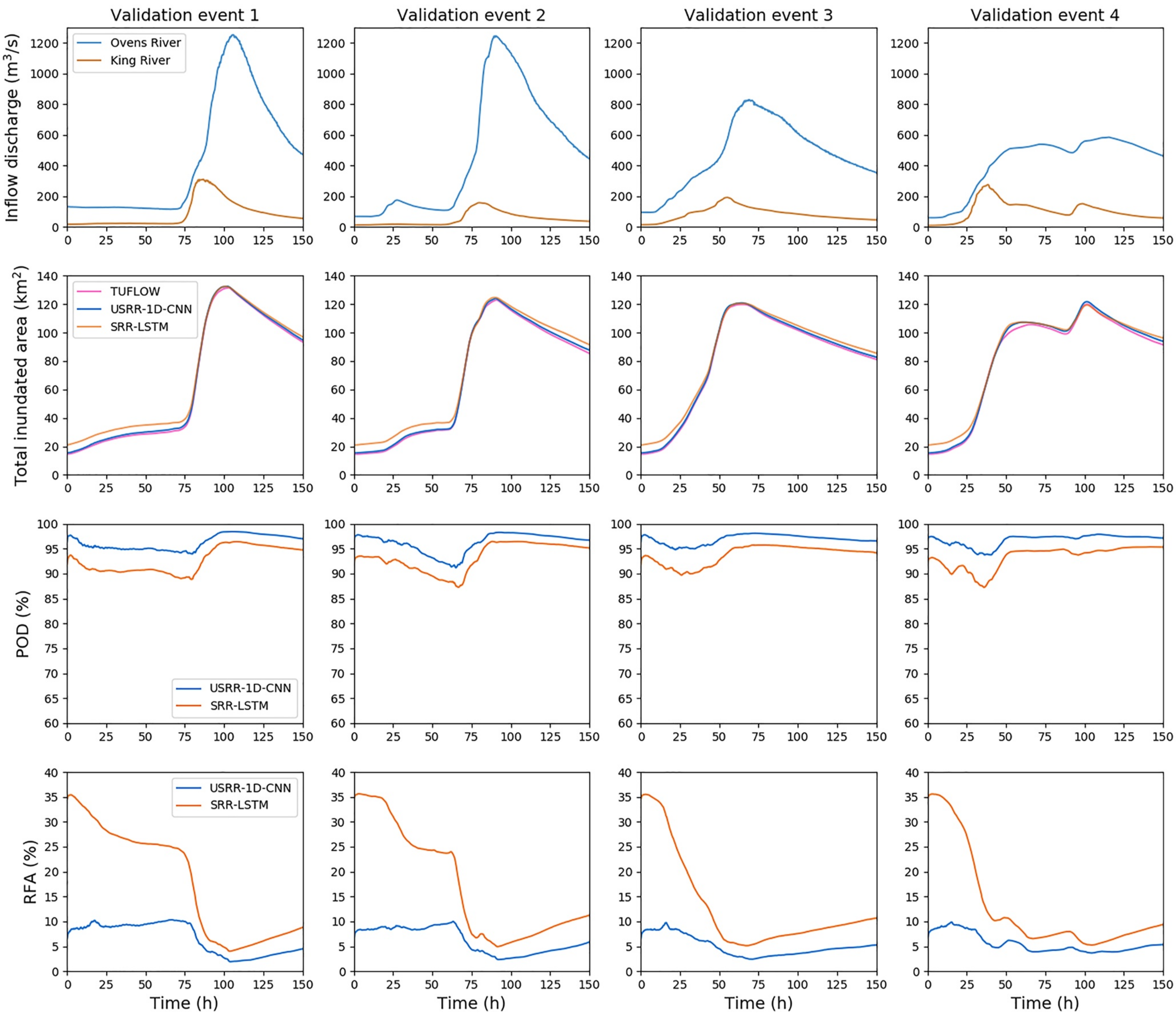

Figure 7. The temporal evolutions of the main inflow discharges, as well as the total inundation area, probability of detection (POD), and rate of false alarm (RFA) for reconstructed inundation extents simulated using U-Net-based spatial reduction and reconstruction-one-dimensional convolutional neural network (USRR-1D-CNN) and spatial reduction and reconstruction-long short-term memory (SRR-LSTM) for four validation events, in comparison with the TUFLOW results.

all training flood events. Therefore, the computational time required by the TUFLOW model is estimated based on this reduced domain with the same number of grid cells simulated using the USRR-1D-CNN approach.

The training time required by the USRR-1D-CNN approach consists of the training time for both the 1D-CNN models development and the U-Net model development as part of the USRR method, which are estimated to be 5.8 and 9 hr, respectively. In other words, the model development time for applying the USRR-1D-CNN approach is estimated to be 14.8 hr, given a developed TUFLOW model and pre-computed flood events. For simulating flood events, the USRR-1D-CNN approach takes 6.18 min to produce 600 flood inundation depth maps for a 150-hr-long flood event with outputs at 15-min intervals as shown in Table 4, and is 98 times faster than the TUFLOW model. The speed-up ratio is proportional to the total number of inundation maps that are generated, which means the USRR-1D-CNN approach would be 392 times faster than the TUFLOW model when a 1-hr outputting timestep is used. Inside the USRR-1D-CNN approach, the required computational time for inundation surfaces reconstruction makes a major part of the total required time, while the required time for water depth simulation using 1D-CNN models is negligible.

Table 4
Computational Time and Training Time Required by the U-Net-Based Spatial Reduction and Reconstruction-One-Dimensional Convolutional Neural Network (USRR-1D-CNN) Approach, the Spatial Reduction and Reconstruction-Long Short-Term Memory (SRR-LSTM) Approach, and the TUFLOW Model for Simulating a 150-hr-Long Flood Event With a 15-Min Output Timestep, Creating in Total 600 Inundation Depth Maps

			Computational time for flood event simulation		
Model	Training time for model development		Water depth simulation	Inundation surfaces reconstruction	Total
USRR-1D-CNN	1D-CNN	USRR	0.20 s	6.18 min	6.18 min
	5.8 hr	9 hr			
SRR-LSTM	LSTM	SRR	1.09 s	1.14 min	1.16 min
	23.7 hr	–			
TUFLOW model	–		–		606.3 min

Note. Computational time for TUFLOW model is estimated for a modeling domain with the same number of grid cells as the USRR-1D-CNN approach. CPU spec: Intel(R) Core(TM) i7-8700K @ 3.70ghz with 6 Cores and 32 GB RAM. GPU spec: NVIDIA Quadro P5000 with dedicated memory 16 GB.

Compared to the SRR-LSTM approach developed by Zhou et al. (2021b), the training time for 1D-CNN model development is less than one fourth of the time required by the training of LSTM models as part of the SRR-LSTM approach. Although the LSTM models developed in this study are only one-third the size of the 1D-CNN models, the 1D-CNN models are trained more quickly because the computation for convolutional layers in 1D-CNN models is highly parallelized while the computation for LSTM layers is mostly sequential (Bai et al., 2018; Zhang et al., 2015). The input time series to these models are long sequences of 384 elements which adds computational burden to the sequential processes. Thus, with the acceleration using the GPU, the 1D-CNN models require much less time to train than the LSTM models. Added with the 9 hr of time required to development the USRR method, the USRR-1D-CNN approach is still faster to develop (with total training time of 14.8 hr) compared to the SRR-LSTM approach (with total training time of 23.7 hr), noting that the SRR method does not require training.

Comparing the computational cost for flood event simulations, the USRR-1D-CNN approach is slower in terms of computational speed, taking five times more computational time than the SRR-LSTM approach. The difference is mainly with the time required by the USRR method and the SRR method to reconstruct the inundation surface. The computational time required to reconstruct one single inundation depth map is estimated to be 0.62 s for the USRR method, while that for the SRR method is only 0.11 s. The USRR method developed in this study is slightly slower than the SRR method because the SRR method only uses 2D linear interpolation during reconstruction which makes the process simple and fast. In the USRR method, the direct outputs of U-Net models are images in patches that need to be assembled to form the final inundation map. This extra process in the USRR method takes extra computational costs.

5. Conclusion

DL-based flood inundation emulation models have been developed to overcome the computational burden of 2D hydrodynamic models. It remains a challenge to build emulation models for flat and complex floodplains where many anabranches form during flood events. The USRR-1D-CNN approach (USRR method with 1D-CNN models) developed in this study is used to emulate a 2D TUFLOW hydrodynamic model for flood inundation modeling on flat floodplains with complex flow paths. The USRR method is developed to select representative locations for complex floodplains and to reconstruct the flood inundation surfaces based on water depth information at these locations. The 1D-CNN models are developed to handle the temporal dependency embedded in the flood driving inputs and to simulate the depth information at selected locations.

Despite the complexity of the flood inundation on the flat floodplain, the USRR-1D-CNN approach is much faster and yields an overall RMSE of 0.053 m for the simulated flood water depth when estimates are compared to TUFLOW model results. The detection of flood inundation extents using USRR-1D-CNN is over 93% for the validation flood events and captures over 98% of the maximum inundation extents. The USRR-1D-CNN approach is about 98 times faster than the TUFLOW model when simulating the same flood event. Comparison is also made to the previous SRR-LSTM (spatial reduction and reconstruction with LSTM models) approach introduced in Zhou et al. (2021b). The reconstruction accuracy of the USRR method is significantly improved compared to the SRR method with the use of U-Net model for capturing spatial correlation in water depths. The use of 1D-CNN models for water depth simulation reduces the required training time compared to LSTM models. Overall, the USRR-1D-CNN approach achieves improved performance for all evaluation metrics except for the computational burden. After being accelerated using GPU, the SRR-LSTM simulation speeds increase and are five times faster than USRR-1D-CNN approach.

As a data-driven modeling method, both the 1D-CNN and the U-Net models employed in the USRR-1D-CNN approach cannot extrapolate beyond the range of training data. This issue can be resolved by generating training data for a wide range of flood conditions and land cover scenarios using 2D hydrodynamic models. For applications where different physical structures such as the construction of flood control levees need to be investigated, it is recommended that models be developed for changed configuration based on "pre-trained" models developed for one scenario to reduce the number of required training events that are generated using 2D models (Hendrycks et al., 2019; Kratzert et al., 2019).

The USRR-1D-CNN approach can be used as a fast emulation model for flood inundation modeling on flat floodplains with complex flow paths. Potential applications include real-time forecasting and engineering design with the consideration of uncertainty.

Data Availability Statement

The USRR method is programmed using the Python programming language (version 3.7) and is freely available at GitHub via https://github.com/yuerongz/USRR-method. The development of U-Net and 1D-CNN models relies on the Python programming language (version 3.7) and the Pytorch Python package (version 1.8.1 + CUDA version 11.1). Data and program used for model development are available at Figshare via http://doi.org/10.26188/20224056 and at GitHub via https://github.com/yuerongz/1D-CNN-model-for-USRR1DCNN-WH.

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