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A 2D hydrodynamic model-based method for efficient flood inundation modelling

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ABSTRACT

Efficient and accurate flood inundation predictions can provide useful information for flood risk mitigation and water resource management. In this paper, we propose a new modelling method, LoHy+, which can be applied to efficiently simulate the spatiotemporal evolution of flood inundation with reasonable accuracy. The method integrates a low-fidelity two-dimensional (2D) hydrodynamic model and a mapping module to estimate water depth in a catchment during floods. The performance of the proposed modelling method was evaluated using a real-world catchment of approximate 2,000 km^2, in the Southern Murray–Darling Basin, Australia. The results show that there is a good agreement between flood inundation obtained from the proposed method and that simulated using a high-fidelity 2D hydrodynamic model. The proposed method is much more efficient than the high-fidelity 2D hydrodynamic model, which makes it an alternative method for applications requiring many model runs or long simulation durations. Also, the LoHy+ model has the potential to be applied in flood inundation forecast, flood risk mitigation design water resource management, etc.

Key words: flood emulation models, flood inundation modelling, hydrodynamic modelling, water management

HIGHLIGHTS

- A new method, LoHy+, is developed to efficiently simulate flood inundation with reasonable accuracy.
- The existing hydrodynamic model is exploited to achieve higher computational efficiency.
- Relationships between flood water evolutions in the river and floodplain are revealed and applied to better achieve the computational efficiency while still guaranteeing the simulation accuracy with the use of LoHy+.

ABBREVIATIONS AND NOTATIONS

LoHy+	The proposed rapid flood inundation model's name
2D	Two-dimensional
DEM	Digital elevation model
LFM	Low-fidelity hydrodynamic model
HFM	High-fidelity 2D hydrodynamic model or existing well-established 2D hydrodynamic model
PCC	Pearson correlation coefficient
SCC	Spearman correlated coefficient
TWD	The threshold water depth value in the river when river water starts flowing out from the river to the floodplain
RWD	The remaining water depth value in the floodplain after the flood is recessed from the floodplain
$RMSE$	Root mean squared error
R^2	Coefficient of determination
POD	Probability of detection
FAR	False alarm ratio
CSi	Critical success index
B	Bias
MDBA	Murray–Darling Basin Authority
CSIRO	The Commonwealth Scientific and Industrial Research Organisation

1. INTRODUCTION

Floods can be devastating for humans. In recent years, floods have caused hundreds of fatalities and billions of dollars of economic losses globally (Verwey *et al.* 2017; Gangrade *et al.* 2019; Yoshida *et al.* 2022). Flood risk management is crucial to mitigate this hazard. This is particularly the case considering climate change, under which there will be increased flood events (Mishra *et al.* 2018; Takeuchi *et al.* 2018; Liu *et al.* 2019; Wu & Leonard 2019; Almoradie *et al.* 2020; Haer *et al.* 2020; Yonehara & Kawasaki 2020). Reliable flood inundation estimation can be useful in providing necessary information, for example, the spatial flood extent and water depth, for developing mitigation strategies and enabling the stakeholders to make better decisions in future flood management and flood risk mitigation strategy design (Henonin *et al.* 2013; Russo *et al.* 2015; Guo *et al.* 2018). Moreover, floods also play an important role in the natural water cycle, and flood inundation estimation enables water resource planners to design better strategies for maintaining healthy ecosystems (Yu *et al.* 2014; Karim *et al.* 2015; Teng *et al.* 2015).

To model flood inundation, three basic approaches have been used, namely two-dimensional (2D) hydrodynamic models, conceptual models, and data-driven models (Hunter *et al.* 2007; Teng *et al.* 2017; Chu *et al.* 2020; Xie *et al.* 2020). Hydrodynamic models are built based on the laws of physics and are widely applied in simulations of flood inundation (Bates & De Roo 2000; Bates *et al.* 2010; Lhomme *et al.* 2010; Bermúdez *et al.* 2019; Wu *et al.* 2020b). By solving the physics-based equations, 2D hydrodynamic models can simulate the spatiotemporal propagation of water flowing in the river channels and across floodplains so that the flood inundation extent, flow velocity, and water depth are predicted. The accuracy of using the hydrodynamic model depends on defining the proper spatial resolution of the mesh and temporal discretisation (Chen *et al.* 2012). High-fidelity simulations can be achieved by using hydrodynamic models with fine spatial and temporal resolutions. However, the high computational cost associated with these models often prevents them from being used for applications requiring a large number of model runs or long simulation duration (e.g., real-time flood forecasting, ensemble flood forecasting or Monte Carlo extreme event estimation) (Ahmadian *et al.* 2018; Kabir *et al.* 2020a, 2020b; Ming *et al.* 2020; Wu *et al.* 2020a, 2020b).

Conceptual models are a type of process-informed models. They mainly use simplified hydraulics theories, for example, the balance of water volume, and model the flood inundation based primarily on digital elevation model (DEM) data, to simulate flood inundation progression with time (Krupka *et al.* 2007; Lhomme *et al.* 2008; Bernini & Franchini 2013; Manfreda & Samela 2019). By including only a few simple processes, conceptual models can be orders of magnitude faster, and they are usually used to estimate the final/maximum flood extent and water depth (Teng *et al.* 2017). Data-driven models are gaining popularity in recent years with the advances in machine learning methods (Bhola *et al.* 2019). In practice, data-driven models need to be developed using a large amount of data from observations and/or simulations and can achieve relatively high efficiency compared to hydrodynamic models (Chang *et al.* 2010, 2018; Chu *et al.* 2020; Xie *et al.* 2020). However, they are not common methods used by flood practitioners. For many flood modellers who are used to hydrodynamic models, such as artificial neural networks, it can save time to develop and implement data-driven models.

In addition, in nations like Australia, there are often well-established 2D hydrodynamic models in many catchments, for example, the Swan River system (Middelmann-Fernandes 2010), Flinders and Gilbert Catchments (Dutta *et al.* 2013), Edward-Wakool System (Vaze *et al.* 2018), Southeast Australia (Kumbier *et al.* 2019). Rather than developing new models, it is worth investigating methods that best utilise existing 2D hydrodynamic models to simulate flood inundation in an efficient manner.

In this paper, we propose a new method, LoHy+, for efficient simulation of flood extent and depth with time using existing 2D hydrodynamic models. The method integrates (1) a 2D hydrodynamic model with coarse mesh (referred to as a low-fidelity model or LFM) to provide low-fidelity estimations of water depth in the river channel and (2) a mapping module to estimate the flood inundation for the entire model domain. The LFM is developed based on an original high-fidelity hydrodynamic model (HFM) by systematically increasing its mesh sizes. The mapping module is developed based on pre-defined relationships between low-fidelity estimations of flood in the river channel and high-fidelity estimations across the entire model domain. The application of this LoHy+ method is demonstrated in a real-world catchment of the Southern Murray–Darling Basin in Australia.

The remainder of this paper is organised as follows: the details of the new method are presented in Section 2; the case used for the study is introduced in Section 3; the results and discussion are presented in Section 4; the advantages, limitations, and the potential applications of the LoHy+ are concluded in Section 5.

2. METHODOLOGY

2.1. The LoHy+ modelling method

2D hydrodynamic models are widely applied in flood simulation. Rather than building new models estimating flood inundation, the LoHy+ method is proposed to efficiently simulate flood inundation utilising existing 2D hydrodynamic models. The LoHy+ method for flood inundation modelling includes two major components: (1) an LFM, which is used to generate low-fidelity water depth estimation in the river channel in an efficient manner and (2) a mapping module, which is used to estimate the flood inundation within the model domain using water depth in the river channel estimated using the LFM.

The purpose of the LFM is to provide information about water depth in the river channel. An LFM is established by coarsening the mesh sizes of an existing well-established 2D hydrodynamic model (i.e., the HFM). The mesh sizes of the LFM are tuned in such a way that its estimated water depth in the river channel shows a good linear relationship with that of the HFM.

A mapping module is established next. It relies on relationships (1) between the LFM river water depth and the HFM river water depth and (2) between the LFM river water depth and the HFM floodplain water depth, to produce estimates of water depth in the model domain. In this mapping module, the relationship of the river water depth between the LFM and HFM is assumed to be linear when the LFM is derived from the HFM. Also, the relationship of water depth between the LFM river and HFM floodplain is identified in a three-stage simplification. Once the mapping module is developed, HFM will not be used in future modelling applications and only LFM will be required, thus improving modelling efficiency.

The modelling process using LoHy+ is shown in Figure 1. The LFM is forced with inputs such as inflows and other boundary conditions, to provide the low-fidelity estimates of water depth in the river. Then, the low-fidelity river water depth data are passed to the mapping module and the estimated flood inundation for the whole model domain can be generated.

2.1.1. Low-fidelity model

An LFM is developed based on an existing HFM by modifying the mesh sizes. The original mesh used in the HFM is coarsened and adjusted to generate the mesh used in the LFM, such that the river water depth simulated by the LFM and HFM can be highly correlated, which is measured using Pearson correlation coefficient (PCC).

The coarse mesh used in the LFM can be generated following the steps below:

- The original mesh resolution of the HFM is systematically decreased to generate the coarse mesh. The resolution in river channels can be set relatively finer compared to that in floodplains.
- The obtained coarse mesh is forced with the same boundary conditions applied in the HFM to generate a low-fidelity estimation of water depth in the river channel. Then, the simulated water depth in the river channel of the LFM and HFM are used to calculate the PCC value to identify river locations where the PCC values are lower.
- In locations where PCC values detected in step (2) are lower than a threshold value (this value is set to be 0.9 in.our case), the coarse mesh is further modified in the neighbourhood (increasing local resolution or/and smoothing mesh) to generate an updated version of the coarse mesh.
- The process of (2) and (3) are to be repeated until the PCC value is above a pre-defined threshold. Also, in this process, the computational time cost is considered to decide if further modification is needed to improve the coarse mesh quality.

Noting that the water can flow out of the riverbanks during this LFM generating process, this is done to guarantee that river water depth simulated by the LFM and HFM can still be highly correlated. In this way, the river water depth simulated by the LFM can be used to estimate the high-fidelity flood water evolution for the whole flood period.

2.1.2. Mapping module

The mapping module is used to estimate the flood inundation of the model domain based on two relationships developed: (1) between water depth in the river channel simulated using the LFM and HFM, respectively, and (2) between water depth in the

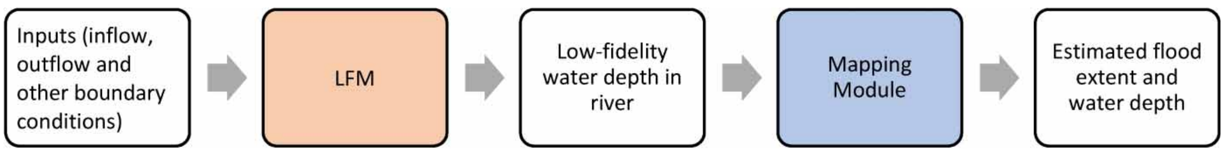

Figure 1 | The proposed new method, LoHy+, for flood inundation modelling.

river channel simulated using the LFM and that across floodplains simulated using the HFM. The first relationship is determined using linear regression between the high-fidelity and low-fidelity water depth at each model cell within the river channel. The second relationship is determined using polynomial regression between the high-fidelity water depth at each floodplain model cell and the low-fidelity water depth at a best-correlated river model cell. The best-correlated model cell within the river channel is identified using Spearman correlated coefficient (SCC): for each model cell on the floodplain, a series of SCC of water depth of this floodplain model cell and its neighbouring river model cells in a given radius area are to be calculated, and the river model cell that has the highest SCC value with the floodplain model cell is chosen as the best-correlated river model cell. However, considering the floodplain can be temporally dry at different model cells during a flood event, it is not reasonable to directly use the SCC for the whole water depth time series to determine the correlated river and floodplain model cells. Therefore, a flood period is divided into three stages based on flood levels across the floodplain as shown in Figure 2 and described below. Only water levels during stage two of flood events are used to develop the relationships.

- Stage one (S1): the water depth on the floodplain is zero for the water stays in the river channel. Water can only flow into the floodplain until the water depth in the river exceeds a threshold water depth in the river (TWD).
- Stage two (S2): the water keeps flowing out from the river to the floodplain and is affected by the water depth in the river channel.
- Stage three (S3): the water depth in the river has fallen below the TWD and the water depth on the floodplain is simulated using a constant value (i.e., ignoring infiltration and evaporation and referred to as the remaining water depth, RWD). The RWD value can be identified via measuring the water depth of the floodplain model cell when the flood evolution is at its recession status for some time (this time can be justified if there is still water flow from the floodplain back to the river channel). At this stage, the connection between the river channel and floodplain is lost.

For each floodplain model cell, at stage S2, the SCC values are to be calculated using the water depth of this floodplain model cell and its surrounding river model cells using flood data during stage S2. There can be many ways to identify the range to search the surrounding river model cells, for example, in this paper's study case (Section 3), only river model cells within a radius of 5 km of this floodplain model cell are considered. The value of 5 km was chosen to set the searching radius due to considering the topography of the study domain. In this way, as many nearest river model cells as possible can be used to identify the river–floodplain relationship with higher accuracy. The river model cell that has the highest SCC value with the floodplain model cell is identified as the best-correlated model cell for the given floodplain model cell.

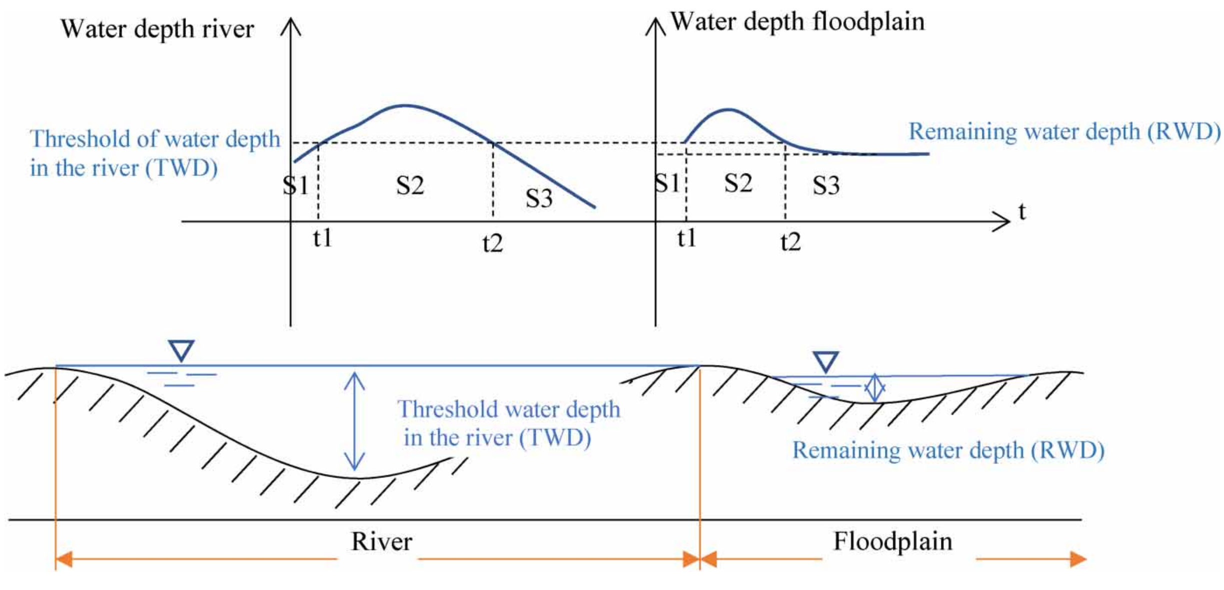

Figure 2 | The three-stage simplification of water depth evolution on the floodplain.

Noting that this paper's study domain is represented using a grid with a resolution of 20 m × 20 m, an overview of the model cells in the river channel and floodplain can be referred to in Figures 5 and 8, respectively. However, due to the study domain area being around 2,000 km^2, one may hardly recognise a single cell if taking a view of the whole study domain.

2.2. Validation of the LoHy+ method

The proposed LoHy+ method for flood inundation modelling is validated in terms of flood depth and spatial flood inundation extent with time, and maximum spatial flood inundation extent over a flood period. The metrics used for evaluating flood depth include the root mean squared error (*RMSE*) and the coefficient of determination (R^2). The formulas to calculate the two metrics are as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2} \tag{1}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2}{\sum_{i=1}^{n}(\bar{Y} - Y_i)^2} \tag{2}$$

where n is the number in the dataset, Y is the value of the high-fidelity data for validation, $\bar{Y}$ is the mean of Y; and $\hat{Y}_i$ is the value of the predicted data from the proposed method for validation.

For the evaluation of the flood inundation extent, four dimensionless metrics, namely the probability of detection (*POD*), the false alarm ratio (*FAR*), the critical success index (*CSi*), and the bias (*B*), are used (McGrath *et al.* 2018):

$$POD = \frac{Hits}{Misses + Hits} \tag{3}$$

$$FAR = \frac{False\ Alarm}{False + Hits} \tag{4}$$

$$CSi = \frac{Hits}{False\ Alarm + Misses + Hits} \tag{5}$$

$$B = \frac{Hits + False\ Alarm}{Hits + Misses} \tag{6}$$

where the *Hits* is the number of cells predicted by both the proposed method and the HFM; the *False Alarm* is the number of cells only predicted by both the proposed method; the *Misses* is the number of cells predicted only by the HFM. Among the four metrics evaluating the performance of the proposed method for flood extent, the values of the *POD*, *FAR*, and *CSi* vary from 0 to 1. If the value of *POD* or *CSi* equals one, the LoHy+ method performs the same with the HFM. Also, if the value of *POD* or *CSi* equals zero, the LoHy+ method's performance is very poor compared to the HFM. While for the value of *FAR*, $FAR = 1$ indicates a bad performance and $FAR = 0$ is for a good performance. For the bias, $B = 1$ suggests the perfect match of the proposed method and the HFM, $B > 1$ means the flood extent is overestimated and $B < 1$ indicates an underestimation of the flood extent by the proposed method.

3. CASE STUDY

3.1. Study area and data

In this study, a catchment in the lower reaches of the Southern Murray–Darling Basin, Australia, is chosen as the case study. The location of the catchment within the Murray–Darling Basin is highlighted in yellow in Figure 3(a). The study area approximately covers 2,000 km^2 with dimensions of 54 km from North to South and 45 km from West to East. This area is characterised by low flood gradients flowing over a broad, flat floodplain terrain with a network of natural and man-made floodplain channels of various sizes. Four main rivers, i.e., the Murray, the Murrumbidgee, the Edward and the Wakool rivers, flow through this area, as illustrated in Figure 3(b).

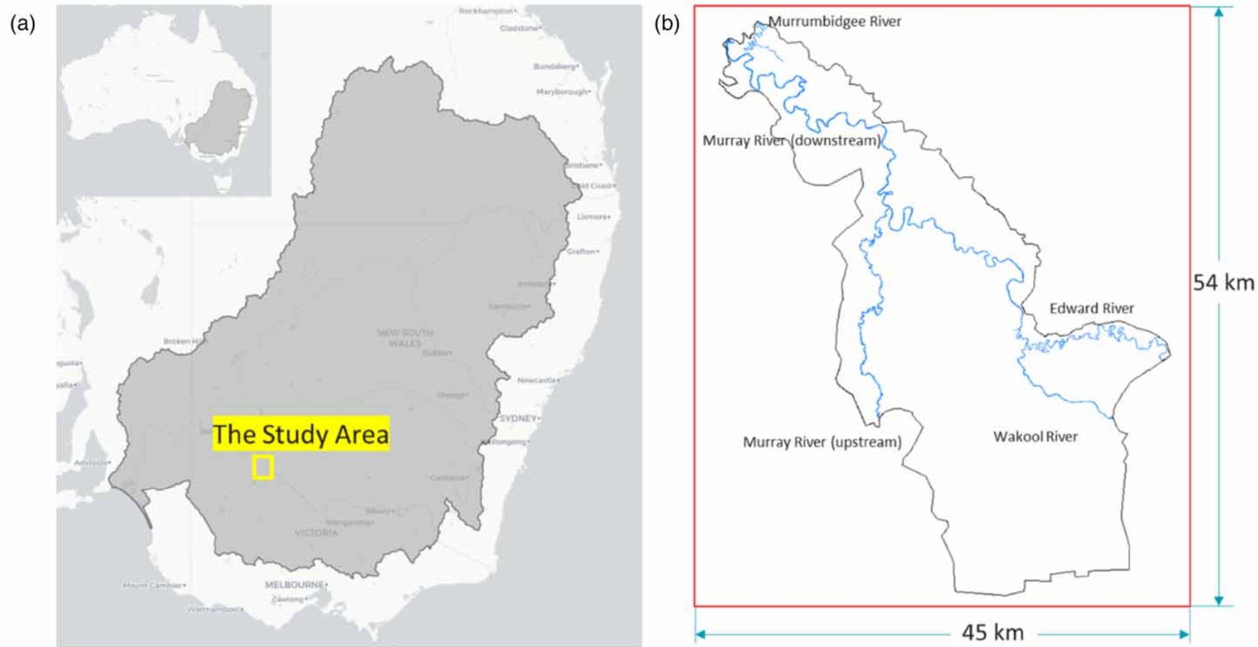

Figure 3 | (a) Location of the study area (highlighted in the yellow square) in the Murray–Darling Basin (represented by grey colour) and (b) study area and the rivers flow through this area. Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/nh.2022.018.

The HFM of the study area was developed by the Commonwealth Scientific and Industrial Research Organisation (*CSI*RO) using MIKE 21 FM for flood inundation simulation. Evaporation and infiltration processes were not considered in this 2D hydrodynamic model. The flexible mesh was chosen to delineate the study area for the numerical simulation and the resolution of the spatial mesh varied from 10 to 200 m. The total number of cells was around 2.4 million. The water depth threshold value for identifying wet/dry cells is defined as 0.1 m in the MIKE 21 FM model. This threshold value of 0.1 m justifying wet/dry cells is chosen to effectively emulate flood inundations considering the horizontal dimension of the study domain (45 km $\times$ 54 km, area 2,000 km^2), and taking a lower value for the dry/wet cells may lead to much more computational cost. More details about the 2D hydrodynamic model of the study area can be found in the report by Vaze *et al.* (2018). The LFM was generated using the method described in Section 2.1.1. The same boundary conditions are used in both the LFM and HFM models for the LoHy+ model development and performance evaluation.

Under the flood inundation simulation capability of the HFM, to cover as many potential inundated locations as possible, synthetic flood data of a 9-month period has been used to develop the relationships as part of the mapping module. These data are developed by scaling-up flood data by 1.1 times from a 7-month period between June and December 2016, and extending the flood period by 30 days before and 60 days after the flood period using historical low flood data to consider low-flow conditions. The scaling value of 1.1 is chosen to get the maximum flood extent in the considered domain without reaching the domain boundaries. For method validation, observed flood data of a 12-month period between May 2010 and May 2011 are used. This flood period is selected due to its multiple rising and falling flood levels, and its smaller flood inundation extent scale compared to the synthetic flood period. The multiple flood levels rising and falling can validate if the three-stage simplification, referred to in Section 2.1.2, evolution works, especially when the water can rise and fall many times during a flood period. The smaller flood inundation extent of the selected validation flood period assures that the validation performs within the simulation capability of the LoHy+ method's developed relationships. Both data sets are shown in Figure 4.

3.2. LFM development

Following the steps listed in Section 2.1.1, the coarse mesh used in LFM is derived by scaling-up the resolution of the cells of the HFM's mesh. This is done in MIKE 21 FM via changing the maximum area value of cells of a flexible mesh. The maximum area value for decreasing the mesh resolution can vary. As for this study's case, we initially scaled up the resolution in

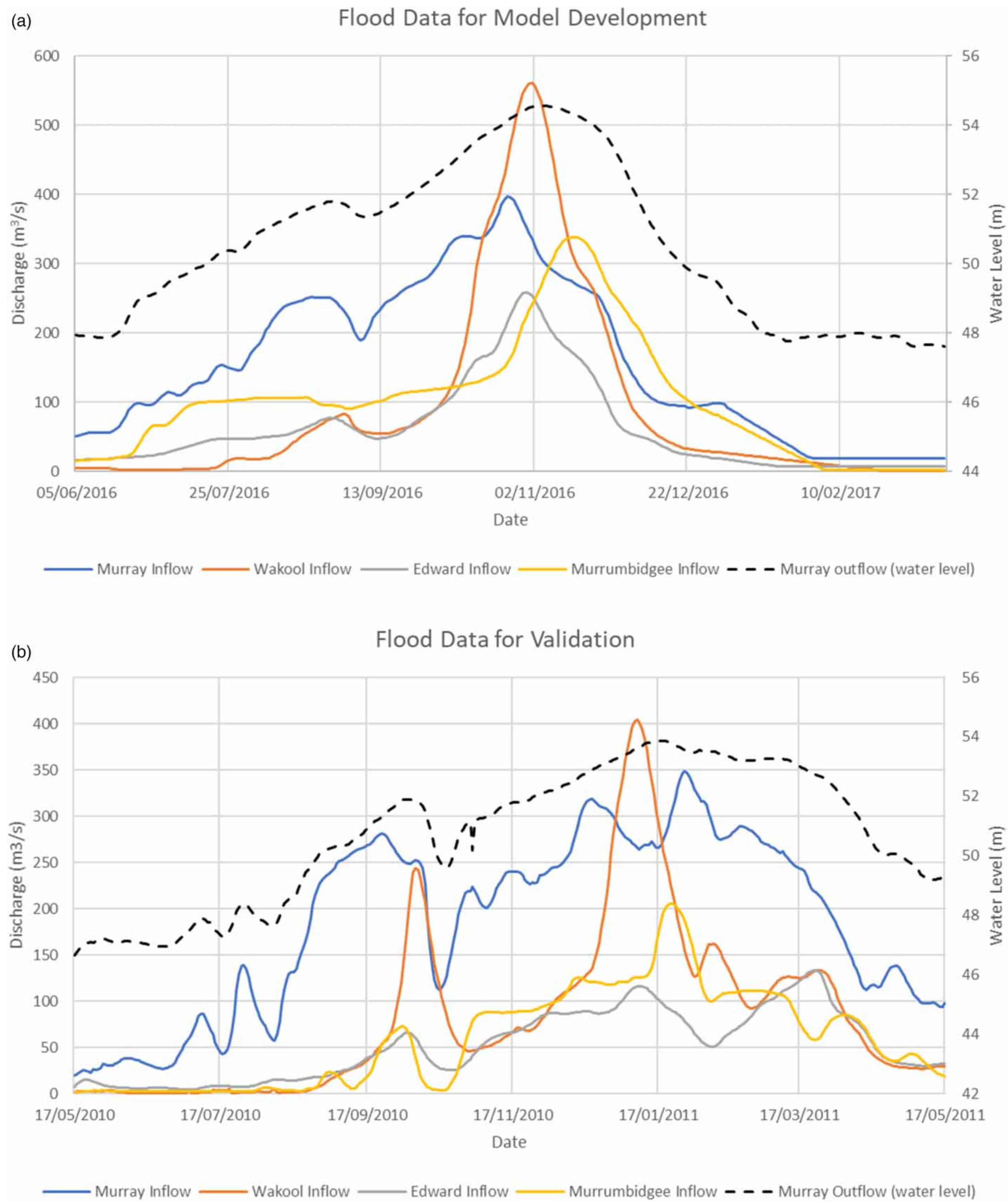

Figure 4 | Data used for (a) model development and (b) validation.

the river to 10 times while the floodplain resolution was set to be the system-default maximum value. Without changing the parameters of settings for computing and the boundary conditions, the first version of coarse mesh was used to generate the flood simulation. Then, the PCC value of water depth simulation in the river between the LFM and HFM was calculated to

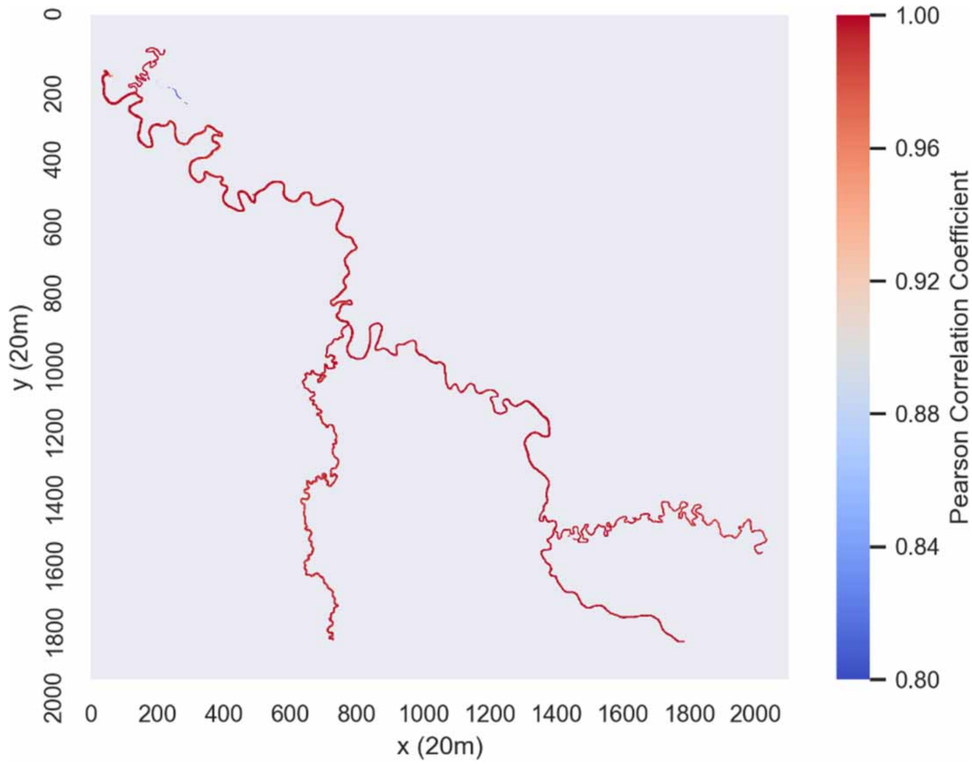

Figure 5 | PCC values of river channel water depth generated using the LFM and HFM.

see if the two sets of data were highly correlated. In our case, we defined the PCC value to identify a highly correlated relationship as 0.9. After comparing PCC values in the river channel, the resolution in the river part of the coarse mesh where the data showed a low value of PCC was slightly increased, and then the second version of the coarse mesh was obtained. The second version of the coarse mesh was again to be simulated, and the PCC between the LFM and HFM was calculated to obtain the third version of the coarse mesh. Similarly, just to repeat the process of simulating, comparing, and modifying the coarse mesh until the final version coarse mesh could be used in the LFM to generate the low-fidelity water depth time series highly correlated with that of the HFM for most of the model cells in the river channel. At the same time, the LFM's computational efficiency was also taken into consideration. In the final version of coarse mesh used in LFM, for almost every model cell in the river channel, the PCC values of water depth between the LFM and HFM were greater than 0.9, which are shown in red in Figure 5. Compared to the original HFM's mesh with around 2.4 million cells, the coarse mesh has just 175,000 cells and can be almost five times faster in simulating the same flood period of data. It needs to be noted that the time spent to set up the LFM may depend on how well one knows about the hydrodynamic model. For the LFM developed and used in this study, we only took around 2 days to derive the LFM from the HFM.

4. RESULTS AND DISCUSSION

The performance of the LoHy+ method for flood inundation modelling was evaluated using the validation flood data of 2010–2011, which is shown in Figure 4(b). The evaluation results are presented in the remainder of this section. The performance of the LoHy+ method evaluated against the original HFM in modelling water depth time series and spatial flood extent is presented in Section 4.1. The efficiency of the LoHy+ method is presented in Section 4.2. The strengths and limitations of this method are discussed in Section 4.3.

4.1. Performance evaluation

The simulation results of the LoHy+ method was validated against that of the HFM in terms of the water depth time series and the spatial flood extent. For evaluation of water depth with time, the *RMSE* and coefficient of determination R^2 across the inundated model cells in the study area are shown in Figure 6. In Figure 6(a) and 6(b), a larger value of the *RMSE* or R^2 is

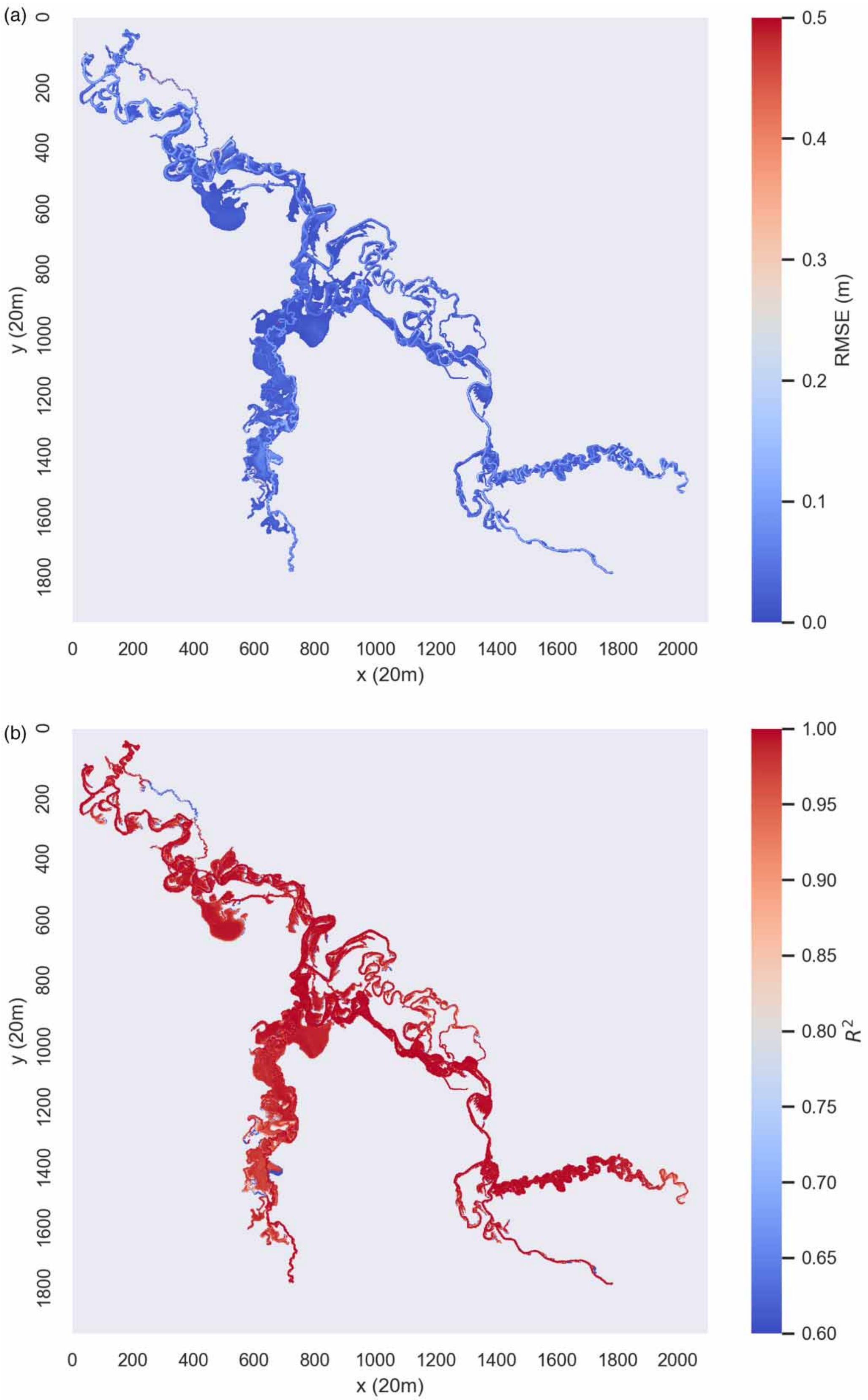

Figure 6 | Performance of simulated water depth over validation period in (a) *RMSE* and (b) R^2.

represented by darker red and a smaller one by darker blue. It is evident from the figure that the proposed method shows a good agreement with the HFM, as for over 95% of the inundated cells the R^2 values are greater than 0.8 and the *RMSE* values are less than 0.3 m, which is very small compared to the dimension of the study area. Though the overall *RMSE* value in different inundated model cells is lower than 0.3 m, it may lead to some errors in predicting the spatial flood inundation extent, for example, in Figures 8 and 9, some edge of the spatial flood inundation extent predicted using the LoHy+ is missed compared to that using the HFM (but the Miss area only takes around 1.44% of the whole flood inundation extent predicted using the LoHy+). It can also be found that the proposed method does not perform well at some edge areas with a relatively smaller value of the R^2 (less than 0.6) while the *RMSE* value is still in a quite small range (0–0.5 m), for example in the southwestern boundary between dry and wet area (shown as the left bottom part in Figure 6(a) and 6(b), the R^2 value is less than 0.6 at the edge while the *RMSE* value is still less than 0.3 m). This is because the water depth at some locations, for example, the flood inundation edge, is usually shallow, and thus the *RMSE* value can be relatively small while the R^2 value can be decreased. The proposed method shows a reasonable accuracy for the prediction of water depth at locations with relatively large water depth.

For evaluating the performance of the LoHy+ method in modelling flood inundation extent, the values of the *POD*, *CSi*, *FAR*, and *B* calculated at 10 days intervals throughout the validation period are present in Figure 7. In Figure 7, it can be found that the proposed method performs well in predicting the spatial flood inundation extent at different stages in the validation flood event. Overall, the proposed method underestimates the spatial flood inundation extent (with the *B* value smaller than 100%) but the *POD* and *CSi* value are greater than 80% and the *FAR* value is less than 8%, which suggest the proposed method can predict the spatial flood extent in a reasonable accuracy. Moreover, taking into consideration the hydrograph of the validation flood event (Figure 5(b)), the proposed method can perform better at high peaks with the *POD* and *CSi* value larger than 90% and the *FAR* value smaller than 8% while the *B* value is closer to 100%. For the period when the values of *POD* and *CSi* are relatively small, the flood is in a recession stage and the floodplain water depth is a constant value (i.e., the remaining water depth). The dynamic of floodplain water is neglected and the LoHy+ can generate different floodplain water depth estimates comparing to the HFM. However, further investigation on this issue is out of the scope of this study paper and should be investigated in the future.

Finally, the maximum flood inundation extent, as well as snapshots of flood inundation extent at six different times during the validation period are illustrated in Figures 8 and 9, respectively. The blue, green, and red colours in Figures 8 and 9 represent *Hit*, *Miss,* and *False Alarm,* respectively. Overall, the LoHy+ performs well in predicting flood inundation extent.

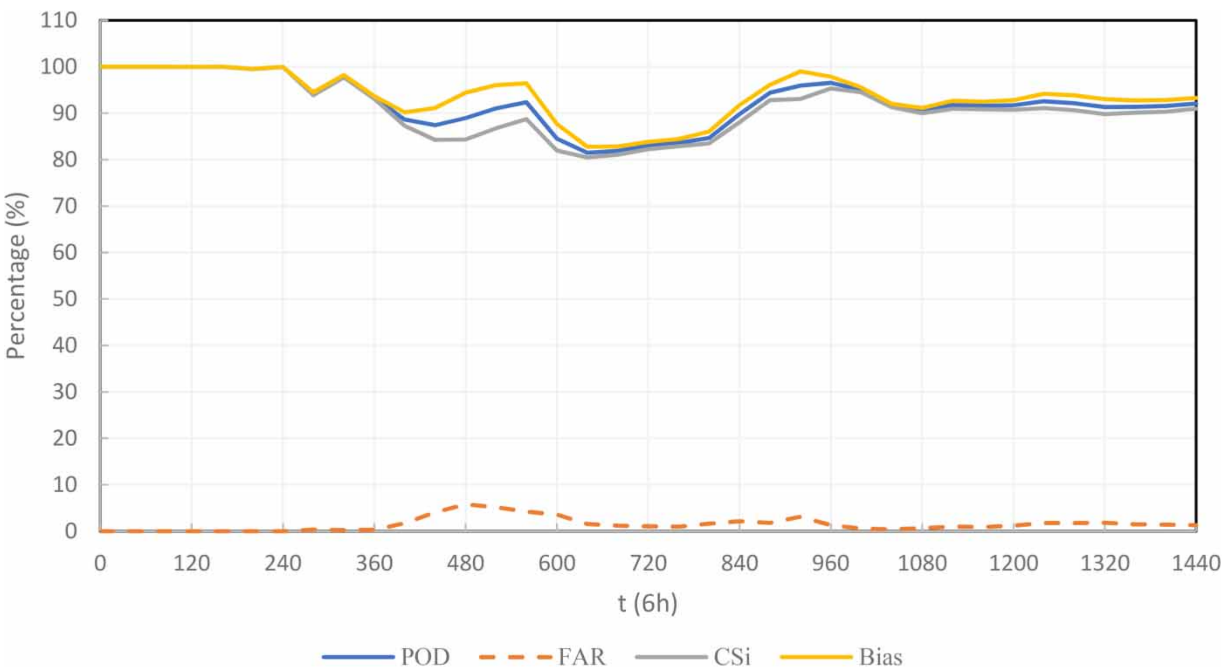

Figure 7 | Flood inundation extent progression at 10-day intervals.

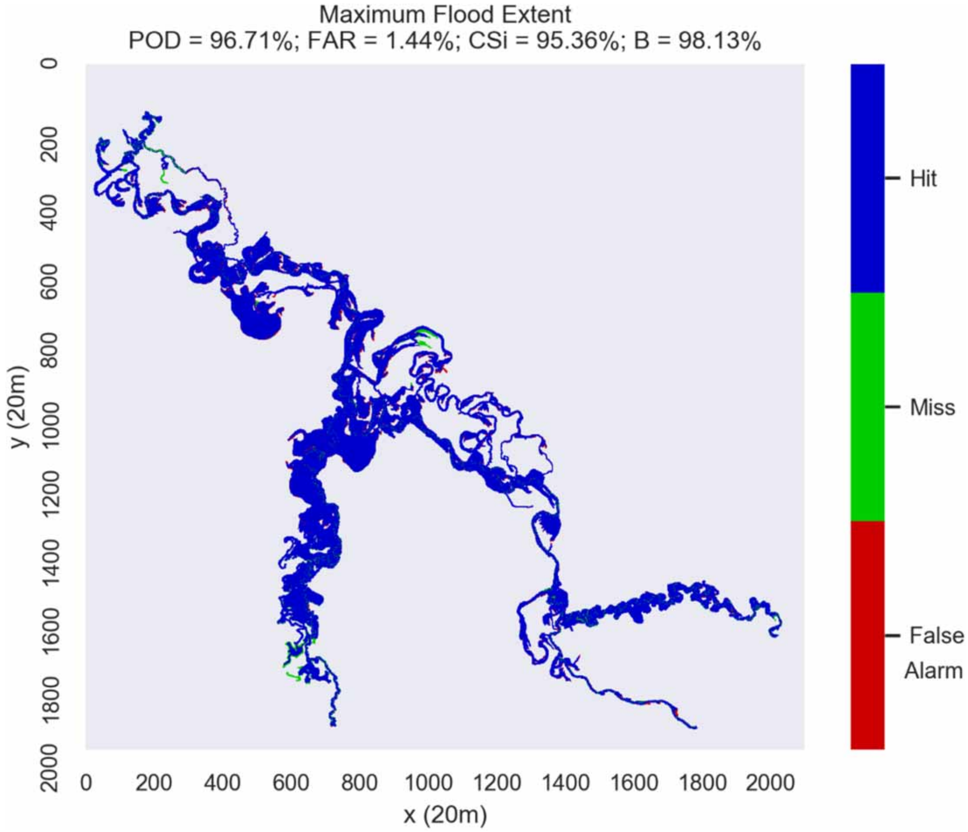

Figure 8 | The maximum flood inundation extent. Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/nh.2022.018.

In Figure 8, the values of *POD*, *CSi*, and *B* are all higher than 95% and the value of *FAR* is below 2%. This indicates that the LoHy+ performs like the original HFM in maximum flood inundation extent simulation. The areas that the LoHy+ cannot predict or lead to false alarms are mainly located at the edge of the whole flood inundation area, where water depth is relatively shallow and there is regular switching between dry and wet conditions. Similar results can be found in Figure 9, where the LoHy+ performs well for predicting flood inundation throughout the validation period at most locations except for the boundaries between dry and wet areas. In shallow water areas, the dynamics scale of flood water can be quite small, and the way we proposed in estimating flood levels over floodplain (Section 2.1.2) can hardly capture it thus false alarms happened in these regions.

In Figure 9(a)–9(f), there are two periods of flood water rising and falling. It can be observed from Figure 9 that the LoHy+ method lags in predicting flood extent during the early stages of a flood period. For example, Figure 9(a)–9(f) shows that in the southwestern region of the study area, the LoHy+ failed to predict inundation during the early stages of the flood. This is because the method relies on the definition of the three stages of floods and the relationships are mainly developed based on flood levels during the second stage. This assumption makes the method to be prone to having larger errors in the initial and final stages of the validation period.

4.2. Computational costs

One important reason the LoHy+ is proposed is to reduce the computation cost of the HFM. The computer used for simulations in this study has an 8-core CPU (Intel Xeon E-2288G CPU), a GPU (Nvidia Quadro RTX 5000) and 64G*B* RAM. The computational time used for simulating the validation event using both methods are compared in Table 1. It can be seen from the table that the proposed method only takes around 16% of the time used by the HFM. The LoHy+ method is approximately five times faster than the original HFM.

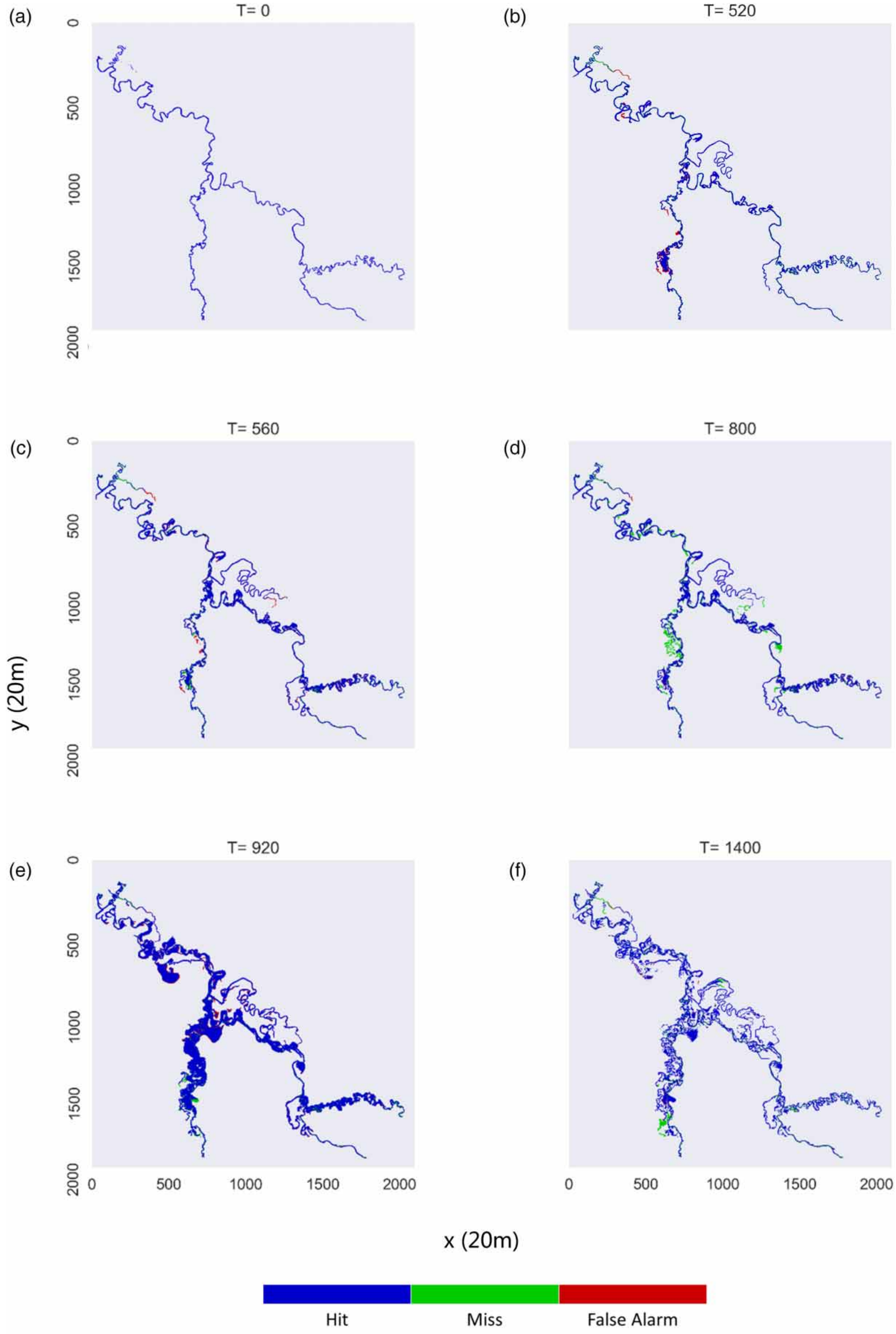

Figure 9 | Comparison of the spatial inundation extent at different dates (*T* represents the time steps and one time step equals 6 h). Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/nh.2022.018.

Table 1 | Time cost for 2010–2011 historical flood simulation of low-fidelity and high-fidelity hydrodynamic models

Models	Flood period simulated	Time consumed in simulation (day)	Fraction of the time compared to HFM (%)
HFM	17/05/2010–17/05/2011	19.3	N/A
LoHy +	17/05/2010–17/05/2011	3.08	16

4.3. Discussion

There are some advantages of the proposed method in emulating the flood inundation. Compared to well-established 2D hydrodynamic models with fine mesh, it has a reasonable performance in terms of the water depth and spatial inundation extent while significantly reducing the computational cost. And the LFM used as part of the LoHy+ method can be easy to be established by simplifying the original 2D hydrodynamic model, which is often available for many major catchments. It is noted that the LoHy+ model needs to re-derive the LFM and recalibrate parameters used in the Mapping module when one wants to use the LoHy+ to predict flood inundation in other different sites. This is the same with one using HFM to simulate flood inundation for other sites. The effort to derive an LFM from an HFM depends on how well one knows about the hydrodynamic model, and it should be much easier to obtain an LFM than to develop a new hydrodynamic model or other types of models from scratch.

Several factors affect the accuracy of the proposed new method for flood inundation modelling – LoHy+. First, the method relies on an artificial classification of floods into three stages (i.e., S1 for no water on the floodplain when water depth in the river does not exceed the threshold value; S2 for water on the floodplain affected by the water in the river channel when water depth in the river exceeds the threshold value; S3 for a constant water depth on the floodplain when water depth in the river falls behind the threshold value), and the relationships between water depth of the LFM in the river and that of the HFM on the floodplain are only developing using data during the second stage (i.e. S2). This led to the time lag or inaccurate floodplain inundation estimation at the initial stages of the flood period, of which there was no dynamic simulation of water rising on the floodplain when water in the river initially flow out of the bank. Second, a constant remaining water depth is assumed in flood stage S3 and this neglects the dynamic process of the floodwater. The floodwater on the floodplain was static and the real inundation extent was not accurately simulated. Thus, discrepancies in water depth of inundated locations on the floodplain generated using the HFM and the LoHy+ method are more pronounced at the final stage. A dynamic remaining water depth method for S3 can be developed to tackle this. Third, a single general linear regression method with one input variable is used to establish the relationship between the water depth in the river and on the floodplain. However, the water depth in one floodplain location can be affected by multiple locations in the river and at different times. Therefore, more complicated mathematical methods, such as multiple regression, and machine learning methods, will be needed and this should effectively improve the performance of the proposed method. And the sensitivity analysis for different parameters of the Mapping module, for example, the searching radius identifying the river–floodplain relationship, can be systematically done for the next stage for investigating the LoHy+ model's robustness and further improve its performance in wider applications for a different type of flood, for example, the flash flood. Four, the LoHy+ may not generate accurate flood inundation when applied to simulate a flood event to a greater extent than the one used for developing the LHM. Using the established LoHy+ in this situation would be like extrapolation and the parameter calibrated for LoHy+ may not be suitable. Finally, the LoHy+ method is proposed based on the characteristics of the long-period (over 7 months) riverine flood that is generally developed. The hydraulic processes are simplified reasonably and do not consider too much about the significant change in flood water evolution in the floodplain. As for modelling complex types of floods, such as flash floods or urban floods, more complicated hydraulic processes simplifications and more variables representing the complex terrain should be investigated before applying the LoHy+ method.

5. CONCLUSIONS

An efficient method to model the flood inundation, LoHy + , is presented in this paper. This method is based on 2D hydrodynamic models, which are commonly used in the industry and often available for important catchments. The LoHy+ method constitutes a low-fidelity 2D hydrodynamic model (LFM) with a coarse mesh and a mapping module. The LFM is used to generate a reasonably accurate estimation of the river water depth. With this estimation, the mapping module based on regression methods can predict the water depth and spatiotemporal flood inundation extent across the entire model domain. Compared to the original high-fidelity 2D hydrodynamic model (HFM), the LoHy+ can be around five times faster while still having reasonable accuracy in our case study. More importantly, it suggests a potential way to efficiently estimate flood inundation via exploiting the existed hydrodynamic model.

The LoHy+ method is validated against the HFM for estimating the water depth time series and spatial flood inundation extent for a different flood event, which is not used to develop the LoHy+ model, in the lower reaches of the Murray–Darling Basin, Australia. The comparisons in the water depth and the spatial inundation extent show good agreement between the proposed method and the HFM, especially during peaks or high-flow flood periods. The results suggest the proposed method is a computationally cheaper way to predict riverine flood inundation with reasonable accuracy and it will be suitable for applications in flood inundation forecast, flood risk mitigation design, water resources management etc., for which the water depth and spatial inundation extent are important.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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