A NEW RAPID FLOOD INUNDATION MODEL

Yang Liu\textsuperscript{1} and Gareth Pender\textsuperscript{1}
\textsuperscript{1}School of the Built Environment, Heriot-Watt University, Edinburgh, EH14 4AS, UK

Abstract: In this study, we propose a new Rapid Flood Inundation Model (RFIM). The purpose of the RFIM is to generate predictions of water depth and flood extent using less computer resource than required by two-dimensional shallow water equation models (SWEMs). To be useful the RFIM must produce predictions that are comparable with those obtained from SWEMs. The model described here is an improvement on previous RFIMs as it dynamically adjusts the head driving the flood flow to account for the rate of flood inflow and the frictional resistance of the floodplain. This allows the RFIM to adapt predictions of inundation extent to surface characteristics to the area over which the water is spreading. Improvements in the technique are demonstrated by application has been applied to an area of urban floodplain in Thamesmead, London, UK. This demonstrates that the method significantly improves the level of agreement between the proposed RFIM and a SWEM when compared with the performance of a previous spreading algorithm.

INTRODUCTION

Two dimensional flood inundation models based on the shallow water equations are widely used in flood risk management. Their growing popularity has arisen due to the availability of remotely sensed digital elevation data and growth in high powered desktop computing facilities (Krupka et al., 2007; Kharat, 2008). At the present time they are considered to give good descriptions of the hydraulic processes controlling flood flows, since they are based on the mathematical conservation laws for both mass and momentum. Through their application to a range of flood management problems, commercial SWEMs such as, TUFLOW, MIKE FLOOD, ISIS2D, Infoworks 2D and SOBEK have been shown to be powerful simulation tools (Liu et al., 2009). Despite their success, application to real-world problems is limited by their computer requirements. That is the simulation time can be excessive (the order of days) at a grid resolution necessary to resolve flows around buildings and other floodplain obstructions can be excessive (the order of days). There are several situations in which these computational demands become prohibitive and in these circumstances computationally efficient rapid flood spreading models have an important role to play. This is particularly true in flood risk analysis (Lhomme et al., 2008), which involves the investigation of a range of loading, multiple defence system states and uncertainty assessment. This type of analysis needs thousands of simulations for each flood event. The computational expensive of SWEMs means it is not feasible to apply them to this type of flood risk analysis and recourse must be made to simpler faster methods.

The concept of RFIMs relies heavily on replacing time consuming simulation models with a simplified model structure that is much faster. The requirements of RFIMs are therefore fast computation linked to sufficient accuracy and numerical robustness. Evaluation of RFIMs, are normally based on two criteria: (1) A good overall agreement of the water depth, and (2) A good overall agreement of the flood extent when compared with SWEMs. As existing RFIMs are based on volume spreading they have the disadvantage that the same volume of water with different inflow hydrographs produces the same prediction. The objective of the present study is to propose a strategy to integrate inflow and hydraulic resistance in the RFIM and make the predictions more comparable with those from SWEMs.

The use of fast models has only recently (Lhomme et al., 2008; Krupka et al., 2007) become a topic of interest. Lhomme et al. (2007) described improvements to the rapid flood spreading model that focused on incorporating additional physical process within the spreading algorithm (multiple spilling and friction). This improved model was applied to a number of different sites (Carlisle, Cumbia, UK; River Brit, Dorset, UK; Boston, East Anglia, UK; River Lee, London, UK) and compared well with simulations obtained using a more complex hydrodynamic model (TUFLOW). The mean deviation, the fit and bias of predicted depths were used to evaluate performance by quantifying the matching of the flood extent from both models. These test results suggested that the RFSM was capable of producing comparable predictions using a computationally less expensive technique (run time typically < 5 s). In particular, they reported that incorporation of multiple spilling and friction effects in the algorithm had a significant benefit in improving the model predictions for flat floodplains.

Similarly, Krupka (2008) proposed a rapid one-direction spilling flood inundation model. The model was divided into two parts: in pre-calculation, an array of flood storage cells is constructed from a digital elevation map (DEM) of the flood risk area. In the inundation routine, a specified volume of flood water is distributed across the storage cells. The water will spread from a cell to its lowest neighbour with a constant extra head. The spatial measure of fit $F$ and the RMSE of flood depth prediction were used to evaluate the performance between TUFLOW and the RFIM. The spatial measure of fit gives the percentage agreement in flood prediction and RMSE gives an indication of agreement in flood depth prediction in these flood cells. The rapid simulation undertaken for the Thamesmead site took less than one
second. Similar flood extent predictions to those by TUFLOW were obtained as long as a reasonable estimate of constant extra head is used (Krupka, 2008).

EXISTING RAPID FLOOD INUNDATION MODELS

The rapid flood inundation model described by Krupka, 2008 consists of two parts: (i) a pre-calculation routine, in which an array of flood storage cells is constructed from a digital elevation map (DEM) of the flood risk area; (ii) and an inundation routine, in which a specified volume of flood water is distributed across the storage cells (Krupka et al., 2007). The pre-calculation process identifies low points on the DEM and expands these outwards in a manner similar to a growing area of ponded water. The size and number of storage cells are controlled by two flood cell parameters – the minimum area of a flood cell and the minimum depth of a flood cell. Figure 1 shows the expansion process. In the inundation routine, the water is spread from the inflow source between cells using a lowest neighbour principle with a constant extra head (see Figure 2).

![Figure 1: An example of expansion process.](image)

The disadvantage of using this RFIMs structure is that the same inflow volume with a different inflow rate will produce an identical prediction of inundation extent and depth. We are therefore proposing a revised technique to integrate inflow rate and flow resistance into the RFIM and make the prediction more comparable with that obtained from a SWEM.

OUR PROPOSED RFIM ALGORITHM

Below we propose a controlled variable extra head version of the RFIM, in which the inflow hydrograph and hydraulic resistance are embedded in the previous RFIM algorithm developed by Krupka, 2008. The variable extra head can be formulated using equation (2) and the extra head can be modified from equation (3) by adding a Manning value to multiply the calibrated constant value $C_2$ in cases where distributed Manning values are appropriate. Equation (2) can be decomposed to equation (3) if we apply the same Manning’s value to the whole floodplain.

$$ \text{Total volume } S = S_1 + S_2 + \ldots + S_n \quad (1) $$

$$ \text{Extra head} = \frac{S}{S} \times C_1 \quad (2) $$

Where $C_1$ is a calibration constant and $n$ is a pre-specified number of outputs in total simulation time (see Figure 3). Predictions are not sensitive to $n$ since the constant $C_1$ is used to adjust the extra head. The extra head for each flood cell can be modified using:

$$ \text{Extra head} = \frac{S}{S} \times C_1 + \sum_{k=1}^{n} M_k \times C_2 \quad (3) $$

![Figure 2: An example of a flood distribution.](image)
Where $C_2$ is a constant value and $M_k$ is Manning value for each pixel in a flood cell and $TN$ is the total number of pixels in the cell.

![Figure 3: An example of how to distribute extra head](image)

The main differences between this approach and the previous RFIM are:

1. The same volume of water but with different inflow hydrographs will produce different inundation extents. This will produce a better comparison with water depth and flood extent predictions obtained a SWEM.
2. The flood extent is predicted during the development of the inflow hydrograph.

**SENSITIVITY ANALYSIS USING THE MORRIS METHOD**

**Model parameters and objective functions**

For comparison purpose we have named the dynamic extra head RFIM technique VEH- RFIM described here and the constant extra head technique CEH- RFIM of Krupka, 2007. A brief description of calibration parameters used is given in Table 1. In order to evaluate the performance of the RFIM, it is necessary to formulate numerical performance measures that reflect the different objectives. Two objective functions (each corresponding to the goodness-of-fit criteria) are formulated as follows (Krupka, 2007):

<table>
<thead>
<tr>
<th>Model parameters</th>
<th>Description</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_{\min}$</td>
<td>Minimum cell plan Area</td>
<td>$500 m^2$</td>
<td>$50000 m^2$</td>
</tr>
<tr>
<td>$D_{\min}$</td>
<td>Minimum cell Depth</td>
<td>$0.1 m$</td>
<td>$2 m$</td>
</tr>
<tr>
<td>$C_1$</td>
<td>Constant value for VEH- RFIM</td>
<td>$0.01$</td>
<td>$1000$</td>
</tr>
<tr>
<td>$C_{1e}$</td>
<td>Constant extra head for CEH- RFIM</td>
<td>$0.001m$</td>
<td>$2m$</td>
</tr>
</tbody>
</table>

$$F_1(\theta) = \frac{\text{Num}(RFIM \cap S_{2DM \text{Model } i \text{Obs}})}{\text{Num}(RFIM \cup S_{2DM \text{Model } i \text{Obs}})}$$

$$F_2(\theta) = \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (h_{RFIM} - h_{TUFLOW})^2}$$

(4)

(5)

Where the $\text{Num}$ function gives the number of members of the set, $S_{RFIM}$ and $S_{2DM \text{Model } i \text{Obs}}$ represent the sets of pixels classified as wet by the rapid flood inundation model and by SWEM or observed data respectively, $i$ is the $i$-th pixel of the domain consisting of $n$ pixels, $h_{RFIM}$ and $h_{TUFLOW}$ are predicted water depths in the $i$-th pixel in rapid flood inundation model and the SWEM or observed data.

**Morris method**
Sensitivity coefficients, which are the partial derivatives of the model states with respect to the model parameters, play an important role in parameter estimation, uncertainty analysis, and model reduction of a hydraulic model. The sensitivity coefficient $S_i$ is calculated from the difference of the nominal and perturbed solutions. In the Morris method (Morris, 1991), two sensitivity measures are used for each factor: $m$, an estimate of the mean of the distribution $S_i(j)$, and $d$, an estimate of the standard deviation of $S_i(j)$. A high value of $m$ indicates an input factor with an important overall influence on the output. A high value of $d$ indicates a factor involved in interaction with other factors or whose effect is nonlinear.

$$S_i = \frac{\partial F(\theta_j)}{\partial \theta_j} = \frac{1}{M} \sum_{j=1}^{M} S_i(j) = \frac{1}{M} \sum_{j=1}^{M} \left| \frac{F(\theta_j + \Delta \theta_j) - F(\theta_j)}{\Delta \theta_j} \right|$$  \hspace{1cm} (6)

where $i$ is the numerical model parameter index.

**EXPERIMENT SETUP AND RESULT**

**Experiment setup**

The RFIM was tested on the Thamesmead floodplain on the River Thames in London. No flooding has been observed in this location in recent history and, therefore, no measured flood data is available. Simulations obtained from a SWEM were therefore used as the basis of comparison. The DEM used is an unfiltered (i.e., buildings are included) on a grid of the 2m resolution. Figure 4 shows the 2m resolution grid digital elevation data and inflow hydrographs for the test site. A value of Manning’s $n$ of 0.04 was used uniformly on the floodplain.

![Thamesmead elevation data and inflow hydrographs](image)

**Figure 4**: Thamesmead 2m resolution grid digital elevation data and inflow hydrograph for each test case.

**Simulated result and sensitivity analysis result**

Figure 5 shows flood extent prediction obtained using TUFLOW compared with that from our proposed VEH-RFIM. The performance statistics of Fit and RMSE are shown in Table 2. The VEH-RFIM has been shown to compare well against TUFLOW for Thamesmead site, producing the predictions in a significantly shorter run time (typically $< 1$s).
Table 2: Performance statistics using VEH-RFIM

<table>
<thead>
<tr>
<th>Final flood extent prediction using for VEH-RFIM</th>
<th>RMSE</th>
<th>Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.05</td>
<td>74.80%</td>
</tr>
</tbody>
</table>

The two objective functions are formulated as single objective function $f = 0.5 \times S + 0.5 \times S^*$ for sensitivity analysis for the VEH-RFIM using Morris method. $S$ and $S^*$ are normalized sensitivity coefficient values between 0 and 1 using the two objective functions ($F_1$ and $F_2$). The constant value 0.5 is the weight for the objective function. We set both equal here since both of them are considered to be equally important. A value of 3% of the parameter values was used for the increment to calculate the sensitivity coefficient. The $M$ is set to 20. Table 3 shows the rank of importance for the 3 parameters according to the Morris measure $m$ using the single objective function. The small rank indicates the parameter is less sensitive and a high value of $d$ value indicates a factor involved in interaction with other factors or whose effect is nonlinear.

Table 3: Sensitivity analysis using the single objective function

<table>
<thead>
<tr>
<th>Model parameter</th>
<th>$m$ of $S(j)$</th>
<th>$d$ of $S(j)$</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_{min}$</td>
<td>0.00000475</td>
<td>0.0000122</td>
<td>1</td>
</tr>
<tr>
<td>$D_{min}$</td>
<td>0.1403</td>
<td>0.4596</td>
<td>3</td>
</tr>
<tr>
<td>$C_1$</td>
<td>0.00009367</td>
<td>0.0000968</td>
<td>2</td>
</tr>
</tbody>
</table>

Comparison with constant head RFIM algorithm

To compare our proposed VEH-RFIM algorithm with previous CEH-RFIM algorithm, we report the results obtained from performing 10 random runs of each algorithm. From Table 4, it can be seen that the performance of VEH-RFIM is much better than CEH-RFIM for flood extent and water depth prediction with respect to the RMSE and Fit. The difference is not significant for the 10 random runs using the VEH-RFIM algorithm. Hence, the VEH-RFIM is not very sensitive to the model parameters and the model parameters are easy to calibrate using a very small number of model runs compared to CEH-RFIM. Initial results show that CEH-RFIM needs about 5000 simulations to get a good result using random a sampling method, which is close to the best result shown in Table 4 using VEH-RFIM.

The VEH-RFIM parameters were automatically calibrated using a single objective particle swarm optimisation (PSO). The two objective functions are formulated as single objective function $Fitness = 0.5 \times F_1 + 0.5 \times F_2$ for calibration using...
the PSO. The constant value 0.5 is the weight for the objective function. We set both equal here since both of them are thought equally important. Sixty iterations were employed as a stopping criterion when a population of $P=50$ was used. The optimal parameters ($A_{\text{min}}=18806, D_{\text{min}}=0.29$ and $C_1=19.99$) were obtained after 60 iterations. The results, including the RMSE and Fit are listed in Table 2. For a more detailed description of particle swarm optimisation algorithm and its applications the reader is referred to Kennedy and Eberhart (1995) and Liu (2009).

**Table 4**: performance statistics using VEH-RFIM and CEH-RFIM

<table>
<thead>
<tr>
<th>Final flood extent prediction using for VEH-RFIM</th>
<th>best</th>
<th>worst</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>0.0508</td>
<td>0.0678</td>
</tr>
<tr>
<td>Fit</td>
<td>74.42%</td>
<td>48.44%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Final flood extent prediction using CEH-RFIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
</tr>
<tr>
<td>Fit</td>
</tr>
</tbody>
</table>

**CONCLUSIONS**

Simulating flood inundation problems usually require a large amount of computation time for high resolution data. The focus of this research was to develop a fast inundation model that produced predictions comparable with those obtained from two-dimensional shallow water equation models. We have proposed a controlled variable extra head version of our previous RFIM, in which the inflow hydrograph and hydraulic resistance are embedded into the previous RFIM. The main advantage is that the rate of flood volume in flow is now accounted for in inundation predictions. The modified RFIM has been applied to Thamesmead site. This experiment showed that by using the new algorithm, the water depth prediction obtained was comparable to that from using TUFLOW. The new RFIM parameter sensitivity has been measured using Morris method. A sensitivity analysis shows that VEH-RFIM predictions are not sensitive to parameters values. The evaluation scheme considers numerical performance measures of two different objectives: (1) flood extent and (2) water depth. Work is currently undergoing to include (i) velocity prediction, and (ii) multi-objective calibration in the RFIM.

**ACKNOWLEDGEMENTS**

The research reported in this paper was conducted as part of the Flood Risk Management Research Consortium. The FRMRC is supported by grant EP/F020511/1 from the Engineering and Physical Sciences Research Council, in partnership with the DEFRA/EA Joint Research Programme on Flood and Coastal Erosion Risk Management, UKWIR, OPW (Ireland) and the Rivers Agency (Northern Ireland). This financial support is gratefully acknowledged. The authors are also grateful to Environment Agency for providing LiDAR the data and the Ordnance Survey for providing Mastermap® data. The comments and advice received from Julian Lhomme, HR Wallingford Ltd are also acknowledged.

**REFERENCES:**


