Real-Time Flood Forecasting Based on a High-Performance 2-D Hydrodynamic Model and Numerical Weather Predictions

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Abstract A flood forecasting system commonly consists of at least two essential components, that is, a numerical weather prediction (NWP) model to provide rainfall forecasts and a hydrological/hydraulic model to predict the hydrological response. While being widely used for flood forecasting, hydrological models only provide a simplified representation of the physical processes of flooding due to negligence of strict momentum conservation. They cannot reliably predict the highly transient flooding process from intense rainfall, in which case a fully 2-D hydrodynamic model is required. Due to high computational demand, hydrodynamic models have not been exploited to support real-time flood forecasting across a large catchment at sufficiently high resolution. To fill the current research and practical gaps, this work develops a new forecasting system by coupling a graphics processing unit (GPU) accelerated hydrodynamic model with NWP products to provide high-resolution, catchment-scale forecasting of rainfall-runoff and flooding processes induced by intense rainfall. The performance of this new forecasting system is tested and confirmed by applying it to “forecast” an extreme flood event across a 2,500-km² catchment at 10-m resolution. Quantitative comparisons are made between the numerical predictions and field measurements in terms of water level and flood extent. To produce simulation results comparing well with the observations, the new flood forecasting system provides 34 hr of lead time when the weather forecasts are available 36 hr beforehand. Numerical experiments further confirm that uncertainties from the rainfall inputs are not amplified by the hydrodynamic model toward the final flood forecasting outputs in this case.

1. Introduction

Flooding is one of the most frequent and widely distributed natural hazards, causing significant losses to human lives and properties every year across the world (Balica et al., 2013). As a result of climate change, more intense precipitation is expected in the warmer future (Intergovernmental Panel on Climate Change, 2014; Kendon et al., 2012), which may consequently trigger more extreme rainfall-induced flood events and increase flood risk. Flood forecasting is an effective means to provide timely hazard information to relevant government decision-makers and practitioners as well as those residents at risk, which plays an important role in flood risk reduction (Carsell et al., 2004).

A lot of effort has been made in the development of forecasting systems for different types of floods, such as fluvial, coastal (Saleh et al., 2017), flash (Hapuarachchi et al., 2011), and snowmelt floods (Blöschl et al., 2008). Regardless of the type of floods being considered, a complete flood forecasting system normally includes at least two components, that is, a model to predict the sources/drivers of flooding, such as precipitation, river flow, and storm surge, and a hydrological or hydraulic model to efficiently simulate the catchment response and flooding processes along the river networks and in the floodplains.

For fluvial flooding, an accurate numerical weather prediction (NWP) model is an essential component of a flood forecasting system to provide reliable prediction of rainfall. NWP models predict the physical processes in the atmosphere using numerical methods that solve the 3-D partial differential equations derived from the relevant physical laws (de Roo et al., 2003). Prior to 1990s, due to the restrictions in computational power, large-scale (global or continental) NWP models were normally run at coarse resolutions of >100 km. In the last few decades, following the improved scientific understanding of weather processes and significant technical breakthroughs in computing technologies, it has now become a common practice to run large-scale NWP models on government-funded supercomputers at ~10-km horizontal resolution. A

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number of weather service centers across the globe develop and operate these large-scale high-resolution NWP models to provide weather forecasts, for example, the European Centre for Medium Range Weather Forecasts (ECMWF) (Palmer et al., 1990), the Meteorological Service of Canada (MSC) (Gauthier et al., 2007), and the U.S. National Weather Service (Fread et al., 1995). These NWP models and their products have been widely used in operational large/medium-scale and short/long-term flood forecasting platforms, such as the European Flood Awareness System (EFAS) (Bartholmes et al., 2009; Thielen et al., 2009) and the Advanced Hydrological Prediction Services (AHPS) (Mcenery et al., 2005) to provide flood forecasts for Europe and the United States. However, for intense and advective rainfall featured with clear spatial heterogeneity, the resolution provided by these large-scale NWP models is still inadequate and higher-resolution NWP forecasts are needed to resolve the local atmospheric and geographical conditions to support more reliable weather and flood forecasting.

Certain regional and short-range models have been developed and operated at kilometer level grids using outputs from the global models as boundary conditions. For example, in the United Kingdom, a unified model (UM) covering the British Isles has been operating for decades by the U.K. Met Office at low resolution for climate predictions and high resolution for regional NWP (Davies et al., 2005). One version of the UM is the U.K. Variable (UKV) resolution model running nationally on a 1.5-km grid for the majority of the domain and stretching to 4 km along the edges. The high-resolution UKV model represents convective processes explicitly rather than parameterizing them like in the global models. It effectively reflects and captures the effects of localized domain features (e.g., mountains) on rainfall patterns. These are all crucial for reliably forecasting intense rainfall. The performance of the UKV model for rainfall forecasting has been significantly improved, compared with the coarse-resolution models (Kendon et al., 2012; Mittermaier & Csima, 2017). The advances in high-resolution NWP provide a great opportunity to substantially improve the current practice in forecasting floods from intense rainfall, which is still a great challenge in research and practice (Bauer et al., 2015).

Prediction of catchment response and the flooding processes induced by rainfall is another essential component in an effective fluvial flood forecasting system, which may involve the use of a wide variety of hydrological or hydraulic/hydrodynamic models (Campolo et al., 1999; Chau et al., 2005; Chiang et al., 2007; Nayak et al., 2005). In addition to those overly simplified statistical approaches, hydrological models are commonly used to predict flooding at a catchment scale (Blöschl et al., 2008; Garrote & Bras, 1995; J. Li et al., 2017; Liu et al., 2005). The output of a hydrological model is typically time series of flow rate in the river channels. Therefore, a hydrological model is usually coupled with a hydraulic model to predict flood inundation if prediction of detailed flood impact outside the river channels is expected (Yamazaki et al., 2011). Hydraulic inundation models are based on the numerical solutions to the full 2-D shallow water equations (hydrodynamic models) or one of their simplified forms (e.g., diffusion-wave models and kinematic-wave models) (da Paz et al., 2011). When it is necessary, a 1-D river routing model may also be used to simulate the flow processes inside river channels and propagate the upstream flood hydrograph predicted by a hydrological model to downstream, which is then coupled with an inundation model to predict flood impact (Chatterjee et al., 2008; Kim et al., 2012; Paiva et al., 2011). However, simulation of floodplain inundation using 2-D models is computationally expensive, and direct prediction of detailed floodplain hydrodynamics in real time is still not a common practice in an operational flood forecasting system.

Therefore, in large-scale operational flood forecasting systems, hydrological models are currently the dominant choice for flood predictions (Kaufeldt et al., 2016). However, a single hydrological model may not be adequate to simulate the flooding process induced by different rainfall events in certain catchments because models calibrated for low flows may not perform well in simulating high flows, and vice versa (Unduche et al., 2018). Moreover, hydrological models are commonly not capable of forecasting the spreading flood dynamics and extents which are important for risk mitigation, and so operational flood forecasting schemes usually involve coupling a hydrological model with hydraulic/hydrodynamic models or their outputs. For example, the Grid-to-Grid (G2G) model (Bell et al., 2007) adopted in the U.K.’s National Flood Forecasting System (NFFS) is not able to predict detailed flood extent and must be integrated with off-line flood simulation results obtained using hydrodynamic models to estimate flood impact. Furthermore, hydrological models do not impose strict momentum conservation in the governing equations and therefore are not able to predict the physical processes of transient flood waves induced by intense rainfall with the required level of accuracy. In this case, a hydrodynamic model is required to reliably predict the physical...
processes of flooding and output spatially and temporally varying water depth and velocity in the model domain (Andreadis et al., 2007; Mignot et al., 2006; Testa et al., 2007), which can be then used to quantify flood impact and inform risk reduction. But the computational constraint of hydrodynamic models hinders their wider application in large-scale flood forecasting.

Following the recent advances in the relevant scientific and technological fields (e.g., data acquisition and high-performance computing), the performance of full hydrodynamic models has been significantly improved in the last decade (Teng et al., 2017). It has been now technically feasible to simulate flood dynamics in large catchments using the state-of-the-art high-performance hydrodynamic models (Sanders et al., 2010). More recently, the high-performance computing power provided by modern graphics processing units (GPUs) has led to a step change in the flood modeling practice (e.g., Smith & Liang, 2013). We are now able to simulate the detailed dynamics of a flood event at a high spatial resolution across an entire city/catchment involving tens of millions of computational cells in real time (Liang et al., 2016; Xia et al., 2019). However, the exploitation of these latest high-performance flood modeling technologies in flood risk assessment and forecasting is still at an embryonic stage, and more research effort is needed (e.g., Plack et al., 2019; Morsy et al., 2018).

With increasing frequency of intense rainfall in the current and future climate scenarios (Thompson et al., 2017), more extreme flood events are expected. The traditional flood forecasting systems based on hydrological models are proved to be mostly reliable on slow-varying catchment response and flooding processes following prolonged rainfall. It is therefore necessary and desirable to exploit the latest high-performance modeling technology and develop a flood forecasting system by directly coupling with a fully hydrodynamic model to forecast the detailed flood dynamics and impact induced by intense rainfall. Driven by the NWP outputs from the UKV model, this paper presents an innovative flood forecasting system that adopts a high-performance fully 2-D hydrodynamic model to predict the full-scale flooding processes from rainfall to inundation. The performance of the proposed forecasting system is tested and confirmed by implementation in a 2,500-km² domain covering the whole Eden Catchment in England to “forecast” the 2015 Storm Desmond flood event.

2. Framework of the Flood Forecasting System

The structure of the proposed flood forecasting system is illustrated in Figure 1, in which the High-Performance Integrated Hydrodynamic Modelling System (HiPIMS) (Xia et al., 2019) is driven by the UKV rainfall forecasts to predict the full-scale flooding processes across a predefined simulation domain (e.g., a catchment or a city). A high-resolution digital elevation model (DEM) of the domain is required to set up HiPIMS for flood simulation. Human-related interventions, for example, flood defenses, are considered when processing the topographic data to create the final DEM. Other relevant datasets including land cover information and soil properties are also required to estimate model parameters. Initial conditions (water depth and velocities in the computational domain) for starting a simulation may be generated by prerunning the model using antecedent rainfall data from observations or UKV predictions. If available, river gauge measurements and other field observations should be used to calibrate and validate the model. The HiPIMS-based flood forecasting system will produce temporal-spatial varying flood depths and velocities across the entire simulation domain, which can then be further processed to produce inundation maps and other necessary flood information for issuing flood warnings. The results can be also used to support flood risk analysis by superimposing the relevant vulnerability and exposure data.

2.1. NWP Model

NWP products from the UKV model (Davies et al., 2005) are used in this work to drive HiPIMS for real-time flood forecasting. Covering Great Britain and Ireland at a resolution of 1.5 km over the central domain and 4 km along the edges (Tang et al., 2013), the UKV model is the highest-resolution model available for short-range weather forecasting in the U.K. and is able to represent most of the convective dynamics without using a convection parameterization scheme (Lean et al., 2008). The operational UKV model has been run in real time since 2010 by the U.K. Met Office, using 3-hourly cycling 3-D variational Data Assimilation (3D-Var) to generate weather forecasts up to 36 hr ahead for release at every 6 hr (Ballard et al., 2016).
The UKV model outputs are deposited at the Centre for Environmental Data Analysis (CEDA) and stored as binary files in the Met Office postprocessing format, which can be converted into the NetCDF format via an open software tool XCONV. The rainfall forecast data are output at gridded format on a rotated latitude-longitude projected coordinate system and can be transformed to the Ordnance Survey National Grid (BNG) reference system at a spatial resolution of approximately 1.5 km, which can be directly used as precipitation inputs to drive HiPIMS for flood simulation.

### 2.2. Hydrodynamic Model

In a flood event, water depth is generally much smaller than the horizontal inundation extent, and the flow hydrodynamics can be mathematically described by the 2-D depth-averaged shallow water equations (SWEs). In a matrix form, the SWEs may be written as

\[
\frac{\partial \mathbf{q}}{\partial t} + \frac{\partial \mathbf{f}}{\partial x} + \frac{\partial \mathbf{g}}{\partial y} = \mathbf{R} + \mathbf{S}_b + \mathbf{S}_f
\]  

where \( t \) denotes the time, \( x \) and \( y \) are the two Cartesian coordinates, \( \mathbf{q} \) is the vector containing the conserved flow variables, \( \mathbf{f} \) and \( \mathbf{g} \) are the flux vectors in the \( x \) and \( y \) directions, and \( \mathbf{R}, \mathbf{S}_b, \) and \( \mathbf{S}_f \) are the source term vectors representing rainfall and infiltration rates, bed slope, and friction effect, respectively. The vector terms are given by

\[
\mathbf{q} = \begin{bmatrix} h \\ u h \\ v h \end{bmatrix}, \quad \mathbf{f} = \begin{bmatrix} u h \\ u^2 h + \frac{1}{2} gh^2 \\ u v h \end{bmatrix}, \quad \mathbf{g} = \begin{bmatrix} v h \\ u v h \\ v^2 h + \frac{1}{2} gh^2 \end{bmatrix}
\]

\[
\mathbf{R} = \begin{bmatrix} R \cdot I \\ 0 \\ 0 \end{bmatrix}, \quad \mathbf{S}_b = \begin{bmatrix} 0 \\ -gh \frac{\partial b}{\partial x} \\ -gh \frac{\partial b}{\partial y} \end{bmatrix}, \quad \mathbf{S}_f = \begin{bmatrix} 0 \\ -\tau_{bx} \rho \\ -\tau_{by} \rho \end{bmatrix}
\]

where \( h \) is the water depth, \( u \) and \( v \) are, respectively, the two depth-averaged velocity components in the \( x \) and \( y \) directions.
and y directions, R represents the rainfall rate, I is the infiltration rate, \( \rho \) is the water density, g is the acceleration due to gravity, and \( \tau_{nx} \) and \( \tau_{ny} \) are the frictional stresses estimated using the Manning formula:

\[
\tau_{nx} = \rho C_f u \sqrt{u^2 + v^2} \quad \text{and} \quad \tau_{ny} = \rho C_f v \sqrt{u^2 + v^2}
\]

(4)

where \( C_f = gn^{2/3} \) is the friction coefficient with \( n \) being the Manning coefficient.

Apart from the Manning coefficient, infiltration rate is another parameter that may influence the simulation results especially when the catchment under consideration is dry. In HiPIMS, infiltration is considered using the Green-Ampt model with the infiltration rate estimated using the following formula:

\[
I = \frac{df}{dt} = K_s \left[ \left( \psi_f + h \right) \frac{\partial \theta_s}{\partial x} + 1 \right]
\]

(5)

where \( f \) is the cumulative infiltrated depth, \( K_s \) is the effective hydraulic conductivity, \( \psi_f \) is the metric suction head at the wetting front, \( \theta_s \) is the saturated volumetric water content, and \( \theta_a \) is the initial volumetric water content.

To predict the transient and complex flow hydrodynamics across different flow regimes that may occur during a flood event induced by intense rainfall, HiPIMS solves the above governing equations using a Godunov-type finite volume numerical scheme as presented in Liang (2010). The numerical scheme has since been further improved by Xia et al. (2017) and Xia and Liang (2018) for accurate and stable simulation of rainfall-induced overland flows and other flooding processes across an entire catchment, including urbanized areas (Liang & Smith, 2015; Q. Li et al., 2020). The model uses a uniform grid to represent the topographic features of the model domain, consistent with the raster grid of the DEM. Since HiPIMS adopts an overall explicit numerical method, the time step of a simulation is controlled by the CFL condition that is related to both cell size and flow velocity (Xia et al., 2019).

In order to substantially improve the computational efficiency for large-scale simulations and real-time forecasting, HiPIMS is implemented and runs on multiple GPUs. GPUs were originally designed to render high-resolution images and videos but have been extensively exploited in scientific computing to speed up sophisticated computational fluid dynamics models in the last decade. Compared with the central processing units (CPUs), GPUs are better suited for repetitive and highly parallel computational tasks and can be used for flexibly performing operations on multiple sets of data. Several parallel computing platforms such as CUDA and OpenCL have been developed to support the development of models to take advantage of the computational power of GPUs (Rawls et al., 1983). In this work, HiPIMS is developed using CUDA to facilitate large-scale flood simulations on NVIDIA GPUs. To enable efficient flood modeling on multiple GPUs, HiPIMS adopts the CUDA block decomposition method as introduced in Sætra and Brodtkorb (2012) to divide the whole computational domain to generate stripe-like subdomains consisting of rows of cells. Computational tasks on each of the subdomains are carried out separately on different GPUs with exchange of data occurring at the overlapping boundary cells at every time step. The time step in each subdomain is decided according to the CFL condition that is related to the maximum velocity and size of the grid cells. The strategy to ease the data exchange process and unify the temporal resolution of flood calculation across the global domain is to adopt the smallest time step returned from the subdomains and synchronize it as the single global time step. The adoption of a single global time step removes the requirements of sophisticated model implementation and extra machine memory and will not affect the overall simulation efficiency of the model.

2.3. Real-Time Simulation and Visualization

The UKV model is currently operated in real time by the U.K. Met Office to produce 36-hr weather forecasts that are released at every 6 hr. A monitoring module is running to monitor the predicted rainfall pattern inside the user-defined domain and download the NWP products from the UKV model once new output data are generated. Based on the forecasted 36-hr accumulated rainfall, a “warning” threshold will be established for the flood forecasting system. The “warning” threshold is empirically selected according to the historical flood records and rainfall observations in the selected catchment to cover potential floods. Once the total rainfall or highest half-hourly rainfall intensity of a 36-hr rainfall forecast is above the warning threshold,
HiPIMS will be activated to run for at least 36 hr until the end of the flooding event, for example, when the water level in river gauges falls back to the normal stages.

The HiPIMS outputs in terms of flood depths and velocities can be released at any moment during a simulation. The instant output is transferred into a KML file and can be visualized in real time on Google Earth or any open-street maps to show flood inundation and impacted areas, for example, buildings, roads, and farmlands. The predicted maximum flood depth and extent for the forecasted event are also output once a simulation is completed, which can be used to estimate potential flood impact/risk.

3. Case Study: The Eden Catchment

The new flood forecasting system is applied to “forecast” a severe flood event induced by the 2015 Desmond storm in the Eden Catchment, England. The 2,500-km² computational domain covering the whole Eden is represented using a DEM of 10-m spatial resolution to support 2-D hydrodynamic flood simulation. This essentially creates a uniform grid with 25 million computational nodes.

3.1. Description of the Study Area

As shown in Figure 2, the Eden Catchment is located in the northwest of England with an approximate area of 2,400 km². The main watercourse in the catchment is the 145-km-long River Eden, which flows from the southeast to the northwest. River Eden has four main tributaries, the Caldew, Petteril, Eamont, and Irthing. Eden is a relatively wet catchment with an annual average rainfall of over 2,800 mm, 3 times of the annual average in England. The largest human settlement in the catchment is Carlisle, which is located at the downstream end of the Eden and has 75,000 residents, consisting of one third of the total population of the study catchment. Carlisle is not only an economic and industrial center of Northern England adjacent to the Scottish Borders but also a popular tourist destination due to its rich Roman heritage and the nearby Lake District National Park (Environment Agency, 2016).

The Eden Catchment is a rapid response catchment subject to frequent fluvial flooding due to its steep topography in the upstream region. The downstream area, including Carlisle, has experienced many serious floods in its history. For example, the devastating floods in January 2005 and December 2015 both brought significant damage to the city. The postevent survey of the flooded area for the December 2015 event is also illustrated in Figure 2. A reliable flood forecasting and warning system is clearly imperative for the area to mitigate flood risk and improve resilience.

3.2. Data Required for the Flood Forecasting System

Data as required by the proposed flood forecasting system include topographical data, land cover maps, and gridded rainfall forecasts. Rainfall observations including gauge records and radar detected data are also necessary to calibrate and validate the weather forecasts. Digital Terrain Model (DTM) representing the height of bare earth surface is the background topographical data and may be acquired from the Digimap OS Terrain 5-m DTM data set (Link 1 in Appendix A). LIDAR Composite Digital Surface Model (DSM), which may be downloaded from the U.K. Environment Agency (EA) website (Link 2 in Appendix A), is merged with the DTM to reflect buildings and key infrastructure (e.g., flood defenses). Neither of these two digital elevation data sets provide accurate underwater bathymetric information although it is essential for reliable simulation of flow dynamics along river channels. Therefore, the EA surveyed river cross-section data sets covering the downstream river courses are integrated to further improve the final DEM.

Land cover information is useful for estimating and adjusting friction and infiltration coefficients in HiPIMS. Land cover information in the study area can be subtracted from the 2015 U.K. Land Cover Map provided by the Centre for Ecology & Hydrology (CEH) (Link 3 in Appendix A). It is a parcel-based land cover map created by classifying satellite data into 21 classes (Rowland et al., 2017), available at a spatial resolution of up to 25 m for the whole United Kingdom. Grassland is the predominant land cover type (72.4%) in the Eden Catchment, and urban and suburban areas only account for 2.7% of the total catchment area.

The rainfall rate forecasted by the UKV model is a grid-based data set at 1.5-km spatial resolution and 15-min temporal resolution. The Met Office NIMROD system provides gridded radar rainfall data that are calibrated to give the best possible estimation of surface precipitation rate at 1-km spatial resolution and 5-min temporal resolution, which is available in the CEDA archive (Link 4 in Appendix A). It is produced based on
radar records and processed using optimized quality control and correction procedures (Met Office, 2003). Therefore, the NIMROD radar data are treated in this work as the reliable/accurate rainfall observations on the ground. The grid-based rainfall forecasts are also compared with the point-based rainfall observations recorded in the surface weather stations, available from the Met Office Integrated Data Archive System (MIDAS). In the Eden Catchment, five stations, as shown in Figure 2, have hourly rainfall records, which can be downloaded from the CEDA archive.

River gauge measurements and postevent investigations provide crucial data to evaluate the flooding forecasting results and confirm the performance of the hydrodynamic model. The EA flood-monitoring application programming interface (API) provides near real-time measurements of water level and flow rate for rivers across England (Link 5 in Appendix A), and 16 river gauge stations are available in the Eden Catchment (as shown in Figure 2). The EA Historic Flood Map data set provides records of flood extents for historical events in England (Link 6 in Appendix A). These data sets provide valuable information to evaluate the performance of the model in predicting water level hydrographs and inundation extents.

4. Results

In this section, the proposed flood forecasting system set up for the Eden Catchment is tested by reforecasting a severe flood event that occurred on 6 December 2015. The event was caused by the intense rainfall brought by Storm Desmond from 4 to 7 December. The amounts of rainfall in one day and two consecutive days both set new historical records in the catchment, as did the water levels and flow rates at some river gauges, such as Sheepmount, on the River Eden (Environment Agency, 2016). The extreme rainfall event led to severe flooding across the catchment, bringing widespread damage and impact to the city of Carlisle.

To validate the current flood forecasting system, numerical rainfall predictions produced by the UKV model are first compared with radar and gauge observations, and the model outputs from HiPIMS driven by radar rainfall inputs are evaluated against the observed flood extent and measured water levels. Then the performance of the flood forecasting system is demonstrated by directly using the UKV numerical rainfall predictions.
predictions as the model inputs. A computer server equipped with \( 8 \times \) NVIDIA Tesla K80 GPUs is fully exploited to run the hydrodynamic simulations.

### 4.1. Performance of the UKV Model: Numerical Rainfall Predictions

The UKV rainfall predictions are compared first with the NIMROD radar rainfall records for the selected event. The catchment experienced the most intense rainfall from 21:00 on 4 December to 9:00 on 6 December 2015. The grid-based 36-hr accumulated radar rainfall and forecasted rainfall are plotted and compared in Figure 3. The high-intensity zone (the region appears in blue on the maps) of the UKV forecasted rainfall is slightly askew to the northeast direction, compared with the radar rainfall. The heavy rainfall belt forecasted by the UKV model is located more toward the Eden Catchment as outlined by the red line, which essentially means the UKV model overpredicts the rainfall in the catchment. This is further confirmed by the box plots of hourly rainfall rates for all grid cells inside the catchment, as shown in Figure 4. The box plots effectively illustrate the statistical behavior of rainfall rates throughout the 36-hr duration: Box height indicates the spatial variation of rainfall rates. Clearly, the UKV forecasted rainfall is spatially more divergent than the NIMROD radar rainfall. In the first 31 hr, the hourly means, as indicated by the red segment in each of the boxes, of the forecasted rainfall are generally higher than those of the radar rainfall. The forecasted rainfall is almost 0 in the last 5 hr, while the radar observations still show significant rainfall. In general, the UKV forecasted rainfall is higher than the radar rainfall for both the mean and the median values in the entire catchment, which may overpredict the following flood hazard.

Rainfall observations from the surface weather stations are also used to evaluate the quality of the grid-based rainfall forecasting data. Figure 5 compares the UKV predictions and NIMROD radar rainfall with the gauged observations in the five rainfall stations as indicated in Figure 2. It should be noted that the records from the WARCOP RANGE station have missing data in the middle of the event. Except for the SPADEADAM NO 2 station in the northeast of the catchment, the gauged rainfall rates are generally lower than the forecasted rates but higher than the radar records, which is consistent with the previous conclusions. Nonetheless, the numerical rainfall predictions from the UKV model are still considered to agree reasonably well with the radar rainfall and the gauged records in terms of spatial distribution, intensity, and also temporal pattern.

### 4.2. Validation of HiPIMS

Unlike the hydrological models that must rely on many empirical parameters for flood prediction, HiPIMS, as a hydrodynamic model, contains only the infiltration rate and Manning coefficient as the two essential parameters to be determined. The water level recorded at river gauges during the Storm Desmond flood event between 21:00 on 4 December and 12:00 on 7 December 2015 is used to calibrate and validate HiPIMS for flood modeling and forecasting in the Eden Catchment. As introduced in section 2.2, HiPIMS...
uses the Green-Ampt model to estimate the infiltration rate. However, due to substantial antecedent rainfall, the catchment was already wet and saturated when the major flood event started (Environment Agency, 2016), suggesting that the infiltration is relatively small and may be neglected during the intense rainfall-induced flood event. To avoid extra model calibration and reduce the requirement of data related to soil conditions, the infiltration rate is set to 0 for the simulations considered in this work.

The NIMROD rainfall radar data are used to drive HiPIMS on a 10-m uniform grid for model calibration and validation. Initial conditions of water depth and velocity inside the computational domain are also needed to set up HiPIMS; these were obtained by prerunning HiPIMS on a dry domain using 3 days of antecedent radar rainfall data. Land cover in the Eden Catchment is dominated by grassland, and so only two values of the Manning coefficient are used in the simulations, one for rivers/channels and another for other areas. In HiPIMS, the Manning coefficient adopts values as suggested in the standard hydraulics textbooks (e.g., Chow, 1959). To calibrate the model, different values of the Manning coefficient ranging from 0.035 to 0.095 with a 0.02 interval are used to reproduce the flood event, and the combination of 0.055 for rivers/channels and 0.075 for the rest of the domain is found to provide the “best fit” prediction.

To evaluate the model performance, water levels measured at a number of gauges are compared with the simulation results. The Nash-Sutcliffe Efficiency (NSE) coefficient is adopted to quantify the degree of agreement between simulated and observed water levels, which is defined as

\[
NSE = 1 - \frac{\sum_i^N (h_i^n - h_i^o)^2}{\sum_i^N (h_i^n - \bar{h}_n)^2}
\]

in which \(N\) is the total number of time steps involved in the simulation, \(h_i^n\) is the observed water level at
time step $n$, $h_m^n$ is the corresponding predicted value, and $\bar{h}_o$ is the mean observed value. $NSE = 1$ represents a perfect match between observations and predictions while $NSE = 0$ indicates that the model predictions are as accurate as the average of the observed data. Obviously, better agreement between the predictions and observations, that is, higher simulation accuracy, is achieved when the value of $NSE$ is closer to 1.

Additionally, the root-mean-square error (RMSE) between the predicted and measured water levels is also calculated to further quantify the simulation error at each of the river gauges:

$$RMSE = \sqrt{\frac{\sum_N (h_m^n - h_o^n)^2}{N}}$$ (7)

A lower RMSE indicates higher simulation accuracy, and a value of 0 means a perfect fit to the data.

In addition to comparing with the in-stream stage measurements, it is also important to know how well the inundation extent is captured by the flood forecasting system. Metrics have been developed and used to quantify the performance of inundation models in predicting flood extents (Bates & De Roo, 2000; Horritt, 2006; Khan et al., 2011; Schubert & Sanders, 2012). A contingency table (Table 1) is used in this work, showing the frequency of “yes” and “no” inundated cells being correctly/mistakenly predicted inside a specified region. In the table, “hit” refers to a flooded cell (as observed) being correctly predicted/forecasted; “miss” implies a flooded cell predicted/forecasted to be not flooded; “false alarm” occurs when a cell that is not hit by flood in reality (i.e., observation) is predicted/forecasted to be flooded; and finally, “correct negative” refers to an unflooded cell (as observed).

![Figure 5. Times series of the UKV forecasted, NIMROD radar, and observed rainfall in the five weather stations.](image)

| Table 1 | A Contingency Table for Verifying Flood Extent Prediction |
|---------|----------------------------------------------------------|
|         | Observed       |                             |                             |
|         | Yes            | No                          | Total                       |
| Forecast| Yes hits       | false alarms                | forecast yes                |
|         | No misses      | correct negatives           | forecast no                 |
| Total   | observed yes   | observed no                 | total                       |
being correctly predicted/forecasted. As a whole, “hits” and “correct negatives” represent correct predictions, while “misses” and “false alarms” give the wrong predictions. Herein, a computational cell is regarded as a flooded cell if the maximum water depth is predicted to be over 0.3 m, which is the threshold of water depth suggested by the EA as likely to cause property flooding (Environment Agency, 2009).

Based on the contingency table, subsequent quantitative scores (Saleh et al., 2017) can be calculated to further assess the performance of forecast, including

$$\text{POD} \text{ (probability of detection)} = \frac{\text{hits}}{\text{hits} + \text{misses}}$$

POD is defined as the ratio between correctly predicted/forecasted flood cells and all of the “observed yes” cells, which is also called “hit rate.” POD ranges from 0 to 1, with POD = 1 returning the perfect forecast.

$$\text{FAR} \text{ (false alarm ratio)} = \frac{\text{false alarms}}{\text{hits} + \text{false alarms}}$$

FAR calculates the ratio between the “false alarms” and all of the “forecast yes” cells, which also ranges from 0 to 1, with the perfect score being 0.

$$\text{CSI} \text{ (critical success index)} = \frac{\text{hits}}{\text{hits} + \text{misses} + \text{false alarms}}$$

CSI returns the ratio between the “hits” cells (i.e., cells being correctly forecasted to be flooded) and the total number of flooded cells, either predicted or observed. CSI varies between 0 and 1, with 1 being the perfect score.

Figure 6 shows the simulated water levels driven by the NIMROD rainfall inputs, comparing with the observation records at the 16 river gauges. Although clear discrepancy can be detected at some of the gauges, the
Simulation results are generally consistent with the observations and the rising and falling limbs of the flood hydrograph are correctly predicted at all gauges. The NSE and RMSE are calculated and also shown in the figure to indicate the accuracy of the modeling results. For the four gauges at the downstream part of the River Eden (Linstock, Sheepmount, Great Corby, and Sands Centre), the returned values of NSE range between 0.85 and 0.95, indicating excellent agreement between the simulated and measured water levels. The NSEs calculated for the gauges in the upper Eden River (i.e., Kirkby Stephen, Great Musgrave Bridge, and Temple Sowerby) vary between 0.78 and 0.83, suggesting slightly less impressive but still satisfactory results. However, the NSEs calculated at the gauges on the tributaries (Caldew, Irthing, and Petteril) are diverse, with high values (NSE ≥ 0.8) obtained for Cummersdale on the River Caldew, and Botcherby and Newbiggin on the River Petteril, but low values at Sebergham on the Caldew and Melbourne Park on the Petteril. This indicates that the performance of HiPIMS reproducing water levels for the secondary rivers or tributaries is less satisfactory. The results are as expected since the spatial resolution of the DEM is still not high enough to resolve some of these secondary river courses with an adequate number of computational cells across their widths. The calculated RMSEs demonstrate similar trends. The RMSEs calculated for the River Eden gauges are mostly <0.5 m. However, the RMSEs in the tributary gauges are again more diverse and range between 0.15 and 0.91 m. In general, the water level hydrographs measured at the river gauges during Storm Desmond are satisfactorily reproduced by HiPIMS through a simulation at 10-m spatial resolution. The simulation results are found to be more accurate in the main river (the Eden) and the lower catchment than in the tributaries and the upper catchment. It should be noted that the largest human settlement, Carlisle, is located in the lower catchment and the water levels at gauges across the city including Sheepmount, Sands Centre, Botcherby Bridge, and Skew Bridge are all reproduced to a high level of accuracy, comparing with the observations. This is important for reliable prediction/forecasting of the resulting flood hazard.

To further assess and verify the simulation results across the spatial domain, a comparison between the simulated and surveyed flood extents is made in Figure 7 for the most impacted areas in Carlisle. The surveyed flood map provided by the EA covers the two most seriously flooded zones in the city center: (1) the area between Skew Bridge and Sheepmount and (2) the area in either sides of Botcherby Bridge and Melbourne Park (Environment Agency, 2016). It can be observed that the surveyed flood extent is correctly reproduced by the current model to a large extent. It should be noted that the postevent flood map survey relies on photographs and videos with location and time information and other evidences.

Figure 7. Maximum inundation map (Carlisle city center) simulated by HiPIMS using radar rainfall inputs.
provided by residents and investigators. This essentially means those areas that are not covered by the surveyed flood map cannot be interpreted as never been flooded during the event. So the surveyed flood map should be used with great care. Due to the population distribution, it is reasonable to assume that the surveyed flood extent is more complete in the populated urban area than the rural area. Therefore, the quantitative comparison between the simulated and surveyed flood extents is only made in the urban area of Carlisle, which is more completely covered by the postevent survey. In the U.K. postcode system, the first part of a postcode has one or two letters indicating a city or a region (i.e., city/region code), followed by one or two numbers; and the city center often has the number “1” alongside the city/region code. Based on this, areas with a postcode starting with “CA1” are selected to represent the city center of Carlisle (see Figure 7) and used as an example to compare the simulated and surveyed flood extents. The CA1 city center area is covered by 105,583 grid cells (10 m × 10 m) in the hydrodynamic model, in which 28,274 cells are predicted to be flooded; that is, the maximum water depths in these cells are over 0.3 m during the event. The performance matrices as introduced earlier, that is, POD, FAR, and CSI scores, are calculated by comparing the simulation result with the surveyed flood extent and counting the cells to quantify hits, misses, false alarms, and correct negatives. As shown in Table 2, both POD and CSI return relatively high scores while FAR is relatively low. As a whole, the results confirm that HiPIMS is capable of predicting extreme flooding from intense rainfall without the necessity of intensive model calibration and that reliable simulation results may be obtained by using standard values as suggested in a hydraulics textbook for the model parameters (e.g., Manning coefficient).

### 4.3. Real-Time Flood Forecasting Using the UKV Rainfall Predictions

The UKV model releases 36-hr rainfall forecasts every 6 hr at 3:00, 9:00, 15:00, and 21:00 each day, covering the entire period when Storm Desmond occurred. To test the proposed flood forecasting system, the UKV rainfall forecast issued at 21:00 on 4 December 2015 is used, which covers most of the period when intense rainfall occurred. The 36-hr rainfall forecast, that is, grid-based rainfall rate, is used to drive HiPIMS to predict the following fluvial flooding process across the whole Eden Catchment.

According to the surveyed flood extent provided by the EA, Carlisle and its upstream region along River Eden are mostly flooded during Storm Desmond (see Figure 7). Apparently, the severity of the flood inundation is closely related to the water level in the nearby river reaches. Therefore, the water level measurements available at the three river gauges located upstream (Great Corby), midstream (Linstock), and downstream (Sheepmount) of the flooded region are selected to evaluate the performance of the flood forecasting system. The observed and forecasted water levels at these three river gauges are compared in Figure 8, together with the calculated NSEs. Generally, the temporal change of the water level is captured reasonably well in all of the three gauges although small overshoot appears in all of the forecasted results. The NSEs are respectively 0.82, 0.72, and 0.76 at Great Corby, Linstock, and Sheepmount, confirming accurate forecasting of the water levels.

![Figure 8](image)

**Figure 8.** Observed and forecasted water levels at Great Corby, Linstock, and Sheepmount gauges.
Correct prediction of inundation extent is crucial to assess flood risk and plan mitigation strategies. Figure 9 illustrates the forecasted inundation maps for Carlisle and the surrounding areas at different output times to depict the flooding process during Storm Desmond. At 6:00 on 5 December 2015, the southwest corner of Carlisle has been flooded, most likely influenced by the River Caldew (Figure 9a). At 12:00, a large part of the city along the River Eden has been inundated although the water depth is still relatively small (Figure 9b). Then 12 hr later at 00:00 on 6 December, the maximum inundation extent has almost been reached, and almost the entire surveyed flood extent has been covered (Figure 9c). This is consistent with the water level hydrographs as presented in Figure 8, in which the water levels at the three gauges all reach their peak values at this moment. Figure 9d shows the final maximum inundation extent obtained throughout the simulation. Quantitative assessment of the flood extent modeling results in the Carlisle city center is given in Table 3, showing a high hit rate and reasonably low false alarm rate.

As the difference between the NIMROD radar rainfall and the UKV forecasted rainfall is noticeable (refer to the discussion in section 4.2), it is necessary to compare the flood modeling results driven by different rainfall sources and confirm the reliability of the flood forecasting outputs. The maximum inundation map obtained with the UKV forecast rainfall (as shown in Figure 9d) agrees well with that produced using radar rainfall (Figure 7). Both of the

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**Table 3**

*Performance of the UKV Forecast Rainfall-Driven HiPIMS in Reproducing the Surveyed Flood Extent in Carlisle With Postcodes “CA1”*

| Total cells | Hits | Misses | False alarms | Correct negatives | POD | FAR | CSI |
|-------------|------|--------|---------------|-------------------|-----|-----|-----|
| 105,583     | 24,369 | 249    | 9,644         | 71,321            | 0.99| 0.28| 0.71|

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**Figure 9.** Forecasted flood inundation maps in Carlisle and the surrounding areas at different output times.
predicted maximum inundation maps are consistent with the EA surveyed flood extent although the forecast appears to predict inundation in a few places that were not flooded according to the EA surveyed map. This is confirmed by the higher hit rate and false alarm rate of the forecast (POD = 0.99, FAR = 0.28, see Table 3) than those calculated against the simulation results driven by radar rainfall (POD = 0.91, FAR = 0.21, see Table 2), which means the forecast may slightly overestimate the actual Storm Desmond flood in Carlisle.

In order to further compare the simulation results obtained using different rainfall inputs, a 63-hr gridded rainfall data set starting from 21:00 on 4 December 2015 is generated to cover the entire duration of the flood event, which consists of the 36-hr rainfall forecast released at 21:00 on 4 December and the first 27-hr of the rainfall rates released 36 hr later at 9:00 on 6 December. Figure 10 presents the water level hydrographs predicted using the different 63-hr rainfall inputs, compared with the corresponding observations at the three selected river gauges. The water levels predicted using the UVK rainfall are found to overpredict the actual water level as observed. However, the water levels resulting from the radar rainfall-driven simulation are generally smaller than both of the forecasted and measured values. The results are to a large extent as expected and consistent with the positive error of the UKV rainfall predictions, as discussed in section 4.1. Table 4 presents the NSEs calculated for the different water levels at the three selected gauges (Great Corby, Linstock, and Sheepmount). The NSEs from the UKV rainfall-driven simulation are consistently smaller than those calculated against the predictions using radar rainfall. This is consistent with the previous analysis and again confirms that the prediction error of the UKV rainfall data leads to less accurate flood simulation results. Overall, all of the NSEs are still calculated to be consistently bigger than 0.7, which are considered to be acceptable.

Considering the computational efficiency, the proposed flood forecasting system only takes 1 hr and 45 min to produce the 36-hr forecast on a 10-m uniform grid covering the 2,500-km² simulation domain (leading to 25 million computational cells) on 8 × NVIDIA Tesla K80 GPUs. This effectively means that, with the NWPs released 36 hr in advance, the current forecasting system can produce a flood forecast within 2 hr, giving more than 34 hr of lead time. According to the Carlisle Flood Investigation Report (Environment Agency, 2016), the earliest flood warning for this event was issued at 13:11 on 5 December 2015, and then a severe flood warning was issued at 17:34 on the same day. Using the flood forecasting system proposed in this work, flood forecasts and subsequent warnings may be available as early as 23:00 on 4 December, almost 1 day before the flood peak arrived at Carlisle.

Compared with the traditional flood forecasting systems based on hydrological models where in most cases only the upstream flow hydrographs are predicted, the proposed hydrodynamic flood forecasting system can provide detailed flood information including water depth, flow velocities, and inundation extents at high resolution across the entire catchment. Such detailed flood information is essential for assessing potential flood impact and allows relevant decision-makers to develop better informed flood mitigation strategies and emergency management plans.

### Table 4

| Rainfall input | Great Corby | Linstock | Sheepmount | Average |
|----------------|-------------|----------|------------|---------|
| UKV forecast   | 0.8796      | 0.7363   | 0.7628     | 0.7929  |
| NIMROD radar   | 0.9078      | 0.8418   | 0.8980     | 0.8825  |

### 5. Discussion

#### 5.1. Trade-Off Between the Spatial Resolution and Forecasting Lead Time

In hydrodynamic flood simulations, the performance of a model is usually sensitive to spatial resolution. Satisfactory flood forecast is
produced by the proposed HiPIMS-based flood forecasting system on a 10-m uniform grid. However, as discussed in section 4.2, the predicted water levels agree more closely with the observations at the gauges in the downstream catchment and the main river course than those in the upstream catchment and tributaries where the river channels are too narrow to be well resolved on a 10-m grid. Furthermore, certain key land surface features, such as walls, dikes, and other flood defenses, may not be well represented by the DEM at the chosen resolution. Therefore, the accuracy of flood forecasts may be further improved if simulations are run at a higher spatial resolution.

To test this hypothesis, a 66-km² subcatchment located at the southeast of the Eden Catchment (see Figure 11a) is selected to conduct further simulations, including a simulation at 5-m resolution. Driven by radar rainfall data, both of the 5- and 10-m simulations use the same model parameters and initial conditions as the aforementioned whole-catchment simulation. The water level hydrographs produced by the 5- and 10-m simulations are compared with the measurements available at the Kirkby Stephen gauge station inside the subcatchment, as shown in Figure 11b. The hydrograph predicted at 5-m resolution observed to agree slightly better with the observations, as confirmed by a higher NSE and a lower RMSE. The two sets of hydrographs are actually similar during the high-flow period but are significantly different at the low-flow sections when the river flow starts to rise at the beginning and fall back to the normal flow condition at the end. The results are to a large extent as expected. River Eden at Kirkby Stephen is around 20 m wide. Comparing with the 10-m DEM, the 5-m DEM can better represent the river geometry and more importantly avoid disconnected courses of small rivers in spatial discretization, leading to better predicted water level hydrographs especially in the low-flow stages when resolving river connectivity becomes more important.

However, a grid of 2 times finer resolution contains 4 times more computational cells, requiring approximately 8 times of runtime for an explicit hydrodynamic model like HiPIMS to finish a simulation when also taking into account the reduced time steps (see Table 5). For flood forecasting, it is crucially important to provide sufficient

![Figure 11.](image-url)
lead time for flood risk mitigation and emergency management. Although a simulation on a 5-m grid may better resolve the domain topography and river geometry and thus produce better results, 14 hr of runtime is needed to complete the 36-hr simulation as considered in the current study, leading to a loss of 12-hr lead time in providing a flood forecast in comparison with the 10-m simulation. The trade-off between spatial resolution and lead time must be carefully considered and evaluated. For the current case study in the Eden Catchment, simulation at 10-m resolution produces satisfactory results and is considered to be the optimum resolution for timely flood forecasting using the current GPU devices. Furthermore, as the runtime of a 36-hr hydrodynamic simulation is shorter than the release interval of the UKV rainfall forecasts, this leaves a certain level of flexibility for calibrating HiPIMS using real-time observations (data assimilation) when available.

5.2. Cascading Uncertainties in the Forecasting System

The UKV model is a deterministic model that produces one prediction in each output. Uncertainties from the UKV model may propagate to HiPIMS and affect the flood forecasts. To evaluate the impact of the cascading uncertainties, rainfall predictions added with ±10% and ±20% of artificial errors are used to drive HiPIMS to produce flood forecasts for comparison and further analysis. The water depth hydrographs at Great Corby, Linstock, and Sheepmount predicted from the four modified rainfall scenarios are compared with the results obtained using the original UKV rainfall predictions (Figure 12). The results show that the effect of rainfall errors on the simulated water depth increases from the upstream to downstream gauges. But the overall errors of disturbed hydrographs are relatively small in comparison with the originally predicted water depths. This is further confirmed by the RMSEs given in Table 6, calculated against the originally predicted water depth at the three gauges. In the table, the relative mean error is calculated by dividing the average RMSE by the mean water depth at the gauge under consideration. The results imply that the uncertainties from the rainfall prediction in terms of intensity are not amplified by the hydrodynamic model toward the flood forecasting outputs in this case.

5.3. Transferability of the Forecasting System

The proposed forecasting system is targeted at predicting intense rainfall-induced flood events, which are predominantly caused by rapid increase of river flows as result of excess surface runoff. Transferability of the flood forecasting system depends on the availability of high-resolution topographic and rainfall input data and the parameterization of the hydrodynamic model, that is, to specify the model parameters for friction and infiltration effects. A fully hydrodynamic modeling approach, such as HiPIMS, commonly parameterizes the friction effect using the Manning coefficient, and satisfactory simulation results can be obtained using stand values suggested by a hydraulic textbook for different types of land covers.

However, deciding the parameters for infiltration is less straightforward. Infiltration rate is influenced by the spatial heterogeneity of the catchment surface and soil, that is, different land covers/soil types, and also the initial soil moisture. In the current implementation of HiPIMS, the infiltration rate is estimated by the Green-Ampt.

Table 6
Simulation Errors Caused by the Disturbed Forecast Rainfall Inputs

| Rainfall error | Great Corby | Linstock | Sheepmount | Average | Relative mean error |
|---------------|-------------|----------|------------|---------|---------------------|
| +10%          | 0.1785      | 0.2289   | 0.3291     | 0.2455  | +4.73%              |
| −10%          | 0.1577      | 0.2168   | 0.3064     | 0.2270  | −4.36%              |
| +20%          | 0.3844      | 0.4731   | 0.6858     | 0.5145  | +9.91%              |
| −20%          | 0.2954      | 0.4208   | 0.5874     | 0.4345  | −8.35%              |

Figure 12. Time histories of water depth obtained using the forecasted rainfall modified with different levels of error.
In summary, the current hydrodynamic model such as those induced by prolonged but less intense monsoon rainfall. The current hydrodynamic model may not be suitable for forecasting long-term flood events that are sensitive to subsurface runoff, such as those induced by prolonged but intense monsoon rainfall. As a crucial step, the classification of saturated and unsaturated zones may be based on the groundwater table and soil moisture condition of a catchment.

An alternative way to increase the applicability of the current HiPIMS-based flood forecasting system for a wider range of hydrological conditions is to integrate HiPIMS with a hydrological modeling system so that the surface runoff is estimated by the hydrological model and HiPIMS is used to simulate the full-scale overland flow and flooding processes. Finally, it should be noted that, due to the specific limitation of HiPIMS in handling subsurface flows (i.e., no explicit consideration of subsurface runoff), the current flood forecasting system may not be suitable for forecasting long-term flood events that are sensitive to subsurface runoff, such as those induced by prolonged but intense monsoon rainfall.

In summary, the current hydrodynamic model-based flood forecasting system is transferable for application in different catchments to forecast flooding from intense rainfall, provided that the following data sets are available to properly set up the model and drive the simulations:

- high-resolution DEMs and spatial data to resolve complex topographic features and river geometry;
- high-quality rainfall forecasts with sufficient lead time and tempo-spatial resolution;
- estimation of the spatial distributions of soil and land cover types, and soil moisture conditions; and
- field observation data, for example, water level, flow discharge, and flood extent, for model calibration and verification.

In addition to data availability, the transferability of the forecasting system is also restricted by catchment size and availability of computing resources. In the current case study, the forecasting system can provide flood forecasts at 10-m resolution within 2 hr in a 2,500-km² computational domain on a computer server fitted with 8 × NVIDIA Tesla K80 GPUs. Application to larger catchments will involve longer simulation times, but it can be reduced by running the model on more advanced high-performance computing facilities. Therefore, the feasibility of the proposed system for real-time applications should be also evaluated by taking into account the availability of computing resources.

### 5.4. Future Development of the Forecasting System

Flood defenses or hydraulic control facilities such as pumping stations, sluice gates, or embankments may significantly influence the flooding process, especially in the urbanized areas. One limitation of the current flood forecasting system is that the current HiPIMS can only represent the static state of the flood defenses or other hydraulic structures, that is, cannot simulate the dynamic processes of defense failure and flood propagation.
mitigation strategies taking place during an event. Hence, the next step of development would be to further improve HiPIMS to directly simulate the operation and potential failure of certain key flood control infrastructure systems, which will have a predominant influence on the evolution of a flood event.

Ensemble modeling has now been widely used and become a general practice in NWP across the world (e.g., Cloke & Pappenberger, 2009). Ensemble techniques have also been applied in hydrological modeling to deal with the uncertainties associated with model parameters, initial and boundary conditions (Jeong & Kim, 2005; Seo et al., 2006). Potentially, an ensemble forecasting system that produces probabilistic flood predictions could provide more reliable future flood information to the public and decision-makers. However, developing and operating an ensemble forecasting system will clearly require much more computing resources to run the model multiple times with various input data and parameters. In the United Kingdom, a short-range ensemble weather forecasting model called the Regional Ensemble Prediction System (MOGREPS) is operated by the Met Office to produce weather forecasts in real time. Therefore, another direction for future development would be to use the MOGREPS rainfall forecasts and further enhance HiPIMS to deliver an ensemble flood forecasting system.

6. Conclusions

Real-time flood forecasting is an effective means to mitigate the negative impact of flooding by providing timely and accurate flood information and warnings to the public and relevant parties. Due to climate change, more extreme floods from intense rainfall have been observed in recent years across the world. Reliable simulation of this type of highly transient flooding process requires the use of fully hydrodynamic models. Most current flood forecasting systems are developed based on hydrological models or coupled hydrological and hydrodynamic models, which are not capable of predicting the flood events induced by intense rainfall to provide reliable forecasts. In this work, a new real-time flood forecasting system has been developed by integrating a fully hydrodynamic model with the NWP outputs produced by the U.K. Met Office’s operational UKV model. The performance of the flood forecasting system has been demonstrated and confirmed by applying it to “forecast” the 2015 Storm Desmond flood across a 2,500-km² domain covering the entire Eden Catchment including the city of Carlisle in England. Running on a uniform grid of 10-m resolution, the flood forecasting system is able to successfully reproduce the water level hydrographs at the downstream river channels (with an average NSE = 0.79), accurately “forecast” the flood extent in the Carlisle city center (POD = 0.99, FAR = 0.28, CSI = 0.71), and provide 34 hr of lead time with the NWP products released 36 hr in advance.

Therefore, this study fills the current research and practical gaps in forecasting highly transient processes induced by intense rainfall. Based on a fully hydrodynamic model, the proposed forecasting system can provide high-resolution forecast of the full-scale flooding process from rainfall to inundation without necessity of using a complex model structure that typically integrates together hydrological models, river routing models, and inundation models. The simplified modeling structure effectively reduces the uncertainties induced by the one-way model coupling strategy and transferring data between models of different types. Also importantly, the produced flood forecasts provide an unprecedented level of spatial and temporal details of the flood process over the entire catchment. Timely and detailed flood forecasts are essential for assessing and mitigating flood risk, and developing effective plans for emergency response, which will subsequently benefit widely those people at risk, government agencies, and other practitioners who are working on flood risk management.

Appendix A: Links to the Data Sources

The links to the data sources used in this work are given as follows: Link 1: DTM data (https://digimap.edina.ac.uk), Link 2: DSM data (https://data.gov.uk/dataset/fba12e80%2010519f%20104be2%2010806f%201041be9e26ab96/lidar%2010composite%2010dsm%20102m), Link 3: land cover data (https://www.ceh.ac.uk/services/land%2010cover%2010map%20102015), Link 4: radar rainfall data (http://badc.nerc.ac.uk), Link 5: river gauge observations (https://environment.data.gov.uk/flood%2010monitoring/doc/reference), and Link 6: surveyed flood maps (https://data.gov.uk/dataset/76292bec%20107d8b%201043e8%20109e98%201002734fd89c81/historic%2010flood%2010map).
Data Availability Statement

The links to the data used in this work are provided in Appendix A. The DTM data are freely available to all users from institutions that have subscribed to the Digimap service. The DSM data, river gauge observations, and surveyed flood maps are open to public users under the U.K. Open Government Licence. Data can also be accessed online (from https://data.gov.uk/). The land cover data are available upon request from the CEH Data Licensing Team (datalicensing@ceh.ac.uk). The radar rainfall data are available upon request from CEDA Archive (http://archive.ceda.ac.uk/).

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