Water Resour Manage (2015) 29:2543–2561
DOI 10.1007/s11269-015-0956-4

# Evaluating the Effects of Inundation Duration and Velocity on Selection of Flood Management Alternatives Using Multi-Criteria Decision Making

**Ebrahim Ahmadisharaf · Alfred J. Kalyanapu · Eun-Sung Chung**

Received: 1 February 2014 / Accepted: 11 February 2015 /
Published online: 22 February 2015


**Abstract** Impacts of flood management alternatives are mostly assessed by inundation depth. Other inundation parameters such as velocity and duration are rarely taken into consideration. In this paper, a multi-criteria decision making (MCDM) based framework is used to analyze the effects of inundation velocity and duration on evaluation of flood management alternatives. The framework incorporates a two-dimensional (2D) flood model, Flood2D-GPU and a spatial MCDM (SMCDM) method, Spatial Compromise Programming (SCP). Flood2D-GPU is employed to simulate floods and SCP is applied to rank a set of flood management alternatives. Assessment of flood management options is conducted with multiple different weight set scenarios. First, alternatives are ranked without consideration of inundation velocity and duration. Then, the importance of these parameters increases and the alternatives are ordered in each weight set and a GIS map showing the best alternative in each grid cell is generated in each case. Best alternative maps (BAMs) are compared to investigate the impacts of inundation velocity and duration on selection of best strategy using $F$ fit measure and $\kappa$ analysis. The framework applicability is illustrated on the Swannanoa River watershed located in the state of North Carolina, US. Case study results indicate up to 49.7 % change of BAM by taking into account inundation velocity and duration. The presented approach addresses the change in selection of flood management strategies resulted by considering other inundation parameters rather than inundation depth. This can potentially reduce the uncertainties associated with the decisions made without consideration of inundation velocity and duration.

E. Ahmadisharaf
Department of Civil and Environmental Engineering, Tennessee Technological University, Cookeville, TN 38505-0001, USA

A. J. Kalyanapu (✉)
Department of Civil and Environmental Engineering, Tennessee Technological University, 1020 Stadium Drive, Box 5015, Cookeville, TN 38505-0001, USA
e-mail: akalyanapu@tntech.edu

E.-S. Chung
Department of Civil Engineering, Seoul National University of Science and Technology, Seoul 139-743, Republic of Korea

**Keywords** Assessment of flood management alternatives · Flood2D-GPU · Spatial compromise programming (SCP) · Inundation velocity · Inundation duration

## 1 Introduction

Floods are the leading reason for life loss among all weather-related disasters (Sun et al. 2014). Loss of life, damages to structures and agricultural fields, and environmental degradation are some examples of flood consequences. From 1980 to 2008, average of 97 million people affected and 196,000 killed by floods annually (United Nations International Strategy for Disaster Reduction 2013). In the US, average of $8 billion in losses and 89 fatalities occur annually due to floods, over the past 25 years (National Weather Service [NWS] 2013). A survey of literature generally suggests that flood hazard is a function of several variables and not only one single parameter (Jonkman et al. 2008, 2013; Dang et al. 2011). Thus, it is not possible to assess flood impacts by considering only one flood parameter and a comprehensive evaluation needs a method that can account for multiple flooding characteristics.

Flood management is complex and multifaceted, affected by different factors, involving various stakeholders, competing alternatives and different tradeoffs (Levy et al. 2007; Schröter et al. 2014). Under these circumstances, multi-criteria decision making (MCDM) can assist flood management by providing a systematic framework to deal with such complex problems. Several MCDM techniques with different capacities can be identified based on the literature. Hajkowicz and Collins (2007) reviewed 61 unique MCDM methods. There has been a vast application of various MCDM techniques in different categories of flood management such as flood risk mapping (Sinha et al. 2008; Meyer et al. 2009; Chen et al. 2011; Zou et al. 2012; Lee et al. 2013, 2014), flood hazard zoning (Fernandez and Lutz 2011; Kourgialas and Karatzas 2012; Stefanidis and Stathis 2013; Radmehr and Araghinejad 2014), assessment of flood management strategies (Willette and Sharda 1991; Bana et al. 2004; Levy 2005), integrated assessment of long-term flood risk management scenarios (Brouwer and van Ek 2004) and flood risk evaluation (Jun et al. 2013; Lee et al. 2015). Main reasons of applying MCDM for flood management are the impacts of these alternatives on various disciplines and factors, as well as the capacity to structure these complex problems into a quantifiable format.

As flood events influence different locations with different intensities and characteristics, spatial analysis of flood impacts should be taken into account. GIS can be coupled to MCDM techniques to enable DMs accounting for spatial variability of floods. There is a growing interest in coupling GIS with MCDM techniques due to the capabilities of GIS in handling wide range of criteria data from different sources (Chen et al. 2011). Using GIS-aided or spatial MCDM (SMCDM) enables decision makers (DMs) to account for spatial variability of flood characteristics, namely, depth, velocity and duration. Application of SMCDM in flood management first appeared in the study by Tkach and Simonovic (1997), in which Spatial Compromise Programming (SCP) was used for the prioritization of flood management options. Considering the needs for spatial dimension of flood management problems, this study uses SCP to rank a pool of flood management alternatives on a cell-by-cell basis.

A review of literature reveals that flood depth is often the primary input for evaluation of flood impacts. Other flooding characteristics such as velocity and duration are often ignored, although they are important for an extensive understanding of the flood influences. Both flood velocity and duration can lead to harmful consequences. High velocity may cause river bank and bed erosion, and long duration can trigger soil erosion and water pollution. All of these may lead to economic loss, people affected, environmental degradation and ecological imbalance. There have been some efforts to show the effects of these flooding characteristics on some flood-related projects. Dang et al. (2011) evaluated flood duration, velocity and depth as the most flood hazard parameters, respectively, for the study area of Red River Delta in Vietnam. Kreibich et al. (2009) showed significant role of flow velocity on structural damages of roads for the Saxony State of Germany. However, the influence on building damages and business interruption were weak to non-existent. Other studies also showed the large uncertainties associated with lone consideration of water depth (Merz et al. 2004) and intimated the significance of other flood components (Citeau 2003; Forster et al. 2008; Pistrika and Jonkman 2010). Nonetheless, in spite of the need for detailed consideration of velocity and duration of flooding in tandem with water depth for satisfactory loss estimation (Dutta et al. 2003), these variables have not received any attention in assessment of flood management strategies.

Wide concentration on floodwater depth may be due to insufficient data about other potential flooding parameters (Jonkman et al. 2008; Kreibich et al. 2009). Another reason may be the ease of obtaining these parameters by two-dimensional (2D) flood models compared to one-dimensional (1D) models but the higher computational time they need. Previous studies mostly employed 1D models (e.g., HEC-RAS) due to ease of use and simplicity. However, floodplain mapping by using these models is subjective and needs post-processing (Kalyanapu et al. 2012). They are not also capable of simulating the lateral diffusion and the results are not adequately accurate, which is mostly due to inaccuracies in cross-section discretization (Kalyanapu et al. 2011; Qi and Altinakar 2012). 2D models have solved this drawback by a higher order of topographic representation including desirable flood pathways as well as existing and planned structures in the simulations (Kalyanapu et al. 2011). Nevertheless, the high computational time and complexity limit application of 2D flood models also. An advanced 2D full dynamic wave flood model, Flood2D-GPU (Kalyanapu et al. 2011), with an extremely lower computational time than other 2D models based on Graphics Processing Unit (GPU) architecture usage, has been developed recently. The present study takes the benefits of Flood2D-GPU and applies it to attain flood characteristics.

The current study investigates the effects of considering inundation velocity and duration on selection of flood management strategies through a SMCDM-based framework using a case study of the Swannanoa River watershed in the state of North Carolina, US. Inundation depth, velocity and duration as well as costs of implementation are considered as decision criteria to evaluate a set of flood management alternatives. By applying multiple weights set scenarios, in which the importance of inundation velocity and duration increases gradually from the first weight set to the last, a best alternative map (BAM) is produced for each case. These maps are compared to explore the changes in selection of best flood management alternative by increasing the significance of inundation velocity and duration. The change addresses a potential uncertainty in flood management decision making problems by ignoring inundation velocity and duration. The study provides stakeholders and DMs with a better understanding of the potential role of these flooding parameters on decision making problems.

## 2 Methodology

The objective of this study is addressed by employing a SMCDM model integrated with a flood model. The framework contains two modules: 1) Flood modeling module; and 2) SMCDM module. In the first module, Flood2D-GPU is applied to simulate floods. In the second module, SCP is used as the SMCDM tool to evaluate impacts of considering inundation velocity and inundation duration on selection of flood management alternatives. The framework is implemented within the widely used ESRI's ArcGIS™ environment. Figure 1 shows schematic diagram of the presented framework. The following sections will explain the details of the above-mentioned modules.

## 3 Flood Modeling Module

The flood modeling module uses a 2D flood model named Flood2D-GPU. Developed by Kalyanapu et al. (2011), it is a 2D numerical flood model, which was coded in NVIDIA's CUDA programming environment. It solves the non-linear hyperbolic shallow water equations using a first-order accurate upwind difference scheme to generate flood depths and velocities. These equations are developed from the Navier–Stokes equations by integrating the horizontal momentum and continuity equations over depth and also referred to as 2D shallow water equations. The non-conservative form of the partial differential equations are:

$$\frac{\partial h}{\partial t}+\frac{\partial uh}{\partial x}+\frac{\partial vh}{\partial y}=0 \quad \text{Continuity equation} \tag{1}$$

$$\frac{\partial u}{\partial t}+u\frac{\partial u}{\partial x}+v\frac{\partial u}{\partial y}+g\frac{\partial H}{\partial x}+\mathrm{gS}_{\mathrm{fx}}=0 \quad \text{Momentum equation in x−direction} \tag{2}$$

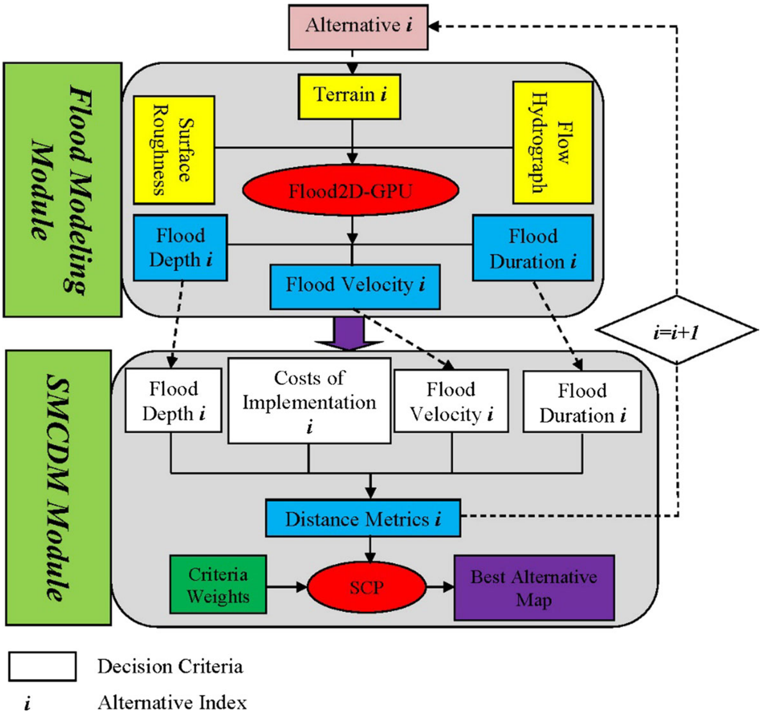



**Fig. 1** Schematic diagram of the presented framework

$$\frac{\partial \mathrm{v}}{\partial \mathrm{t}}+\mathrm{u}\frac{\partial \mathrm{v}}{\partial \mathrm{x}}+\mathrm{v}\frac{\partial \mathrm{v}}{\partial \mathrm{y}}+g\frac{\partial \mathrm{H}}{\partial \mathrm{y}}+gS_{fy}=0 \quad \text{Momentum equation in y−direction} \tag{3}$$

where, $h$ is the water depth, $H$ is the water surface elevation, $u$ is the velocity in the $x$-direction, $v$ is the velocity in the $y$-direction, $t$ is the time, $g$ is the acceleration due to gravity, $S_{fx}$ is the friction slope in the $x$-direction, and $S_{fy}$ is the friction slope in the $y$-direction. The upwind finite difference numerical scheme is used to discretize governing Equations (1–3) as it yields non-oscillatory solutions, through numerical diffusion (Ferziger and Peric 2002). Despite the limitations of the first-order numerical scheme such as incapability in shock capturing, which may lead to flow discontinuities, past successful applications of Flood2D-GPU in various flood simulations such as riverine and dam break flooding, at high spatial results (10–30 m) indicate that artificial diffusion provided by the upwind scheme dampened the shocks and instabilities and at lower courant numbers (Kalyanapu et al. 2011, 2012, 2013, 2014). A staggered grid stencil is used to define the computational domain with the water depth in the center of the cell, and horizontal and vertical velocities on the cell edges. A courant number of 0.15 is used here to avoid model instability problems. The model has been validated for accuracy on the historical failure of Taum Sauk Dam and was also found to provide significantly reduced computational time (by 80–88 times) compared to the same flood model implemented in a Central Processing Unit (CPU)-based environment (based on the estimations by Kalyanapu et al. 2011). The model has been successfully applied in various flood management problems such as flood hazard analysis (Kalyanapu et al. 2012, 2013), flood damage estimation (Kalyanapu et al. 2014) and impact of land use/land cover (LULC) change on floods (Yigzaw et al. 2013).

Required datasets for Flood2D-GPU are: 1) Topography: Digital elevation model (DEM) for terrain representation; and 2) Manning's $n$ for surface roughness: A single Manning's value is used to represent the surface roughness of the entire case study; and 3) Flow hydrograph: A hydrograph at the source location. The output results include raw ASCII files of flow depth and velocity in the $x$ and $y$ directions at various elapsed times during the simulation. These raw results are post-processed using a geospatial toolbox within ArcGIS™ in order to determine maximum flood depth and velocity. A code within MATLAB® is also implemented to determined duration of flooding.

The model is first calibrated with a historical flood event by comparing output flow hydrograph produced by Flood2D-GPU with the observed flow data to calibrate the model. Manning's roughness coefficient is selected as calibration parameter to verify the modeling results. Peak flow and travel time accuracy measures (Schubert and Sanders 2012) are used as performance metrics to measure the model efficiency. These measures are quantified through the following equations:

$$\mathrm{F_Q}=\frac{\mathrm{Q_{Sim}}}{\mathrm{Q_{Obs}}} \tag{4}$$

$$\mathrm{F_T}=\frac{\mathrm{t_{PSim}}}{\mathrm{t_{Pobs}}} \tag{5}$$

where, $F_Q$ is peak flow accuracy measure, $Q_{Sim}$ is the simulated peak flow, $Q_{Obs}$ is the observed peak flow, $F_T$ is travel time accuracy measure, $t_{PSim}$ is the simulated time to peak flow and $t_{PObs}$ is the observed time to peak flow. A $F_Q$ or $F_T$ value of 1.0 refers to perfect agreement, values of greater than 1.0 indicates overestimation and values of smaller than 1.0 shows underestimation.

## 4 SMCDM Module

The produced flood depth, velocity and duration from the flood modeling module are used as inputs to the SMCDM module. In this technique, best alternative is the one, which is closest to the 'utopia'. The 'utopia' is the alternative that provides the best value for each criterion. The closest solutions to the utopia are named compromise solutions and constitute the compromise set. The distance from the ideal solution for each alternative is measured by the distance metric, which is determined based on the following equation:

$$L_j = \left( \sum_{i=1}^{N} w_i^p \left| \frac{f_i^+ - f_{ij}}{f_i^+ - f_i^-} \right|^p \right)^{\frac{1}{p}} \tag{6}$$

in which, $L_j$ is the distance metric for alternative $j$, $f_i^+$ is the utopia for criterion $i$, $f_i^-$ is the nadir for criterion $i$, $f_{ij}$ is the value of criterion $i$ for alternative $j$, $w_i$ is the weight of criterion $i$, $N$ is number of criteria and $p$ is distance parameter varies from one to infinity. Parameter $p$ represents the importance of maximum deviation from the utopia. The selection of $p$ depends on the type of problem and desired solution (Tecle et al. 1998). In this study, $p$ is selected 2 based on the recommendation by Simonovic (1989), which refers to a simple Euclidean distance. Taking this value of $p$, each deviation from the utopia is weighted in proportion to its magnitude.

A MATLAB® code is implemented to apply SCP and to rank the alternatives spatially. Raster files presenting the value of criteria for alternatives are converted to ASCII format to make them compatible for MATLAB® program. Equation 6 is used to determine the distance metric ($L$) in each grid cell. Thus, a spatial map of $L$ is produced for each alternative. Performing a cell-based comparison of the generated maps, the minimum value of $L$ is determined and the associated alternative is selected as best in each grid cell. The output is an ASCII file showing the spatial variability of best alternative.

### 4.1 Comparison Metrics

To interpret the results in a spatial context, the six rasters (BAMs within inundation extent) are compared using two metrics, namely, $F$ fit measure (Horritt and Bates 2001a) and $\kappa$ statistic (Cohen 1960). These two metrics have been previously used in validation studies of flood inundation models (e.g., Yu and Lane 2006). In this study, they are employed for relative comparison of different BAMs. The two measures can be computed by the following expressions:

$$F = \frac{n_n(i \cap j)}{n_{Wet}} \tag{7}$$

$$K = \frac{P_0 - P_C}{1 - P_C} \tag{8}$$

where, $F$ is $F$ fit measure, $n_{n(i \cap j)}$ is the number of grid cells that alternative $n$ is best in both weight set $i$ and $j$, $n_{Wet}$ is total number of wet cells, $\kappa$ is coefficient of agreement, $P_0$ is the proportion of wet cells that are in agreement in two different weight sets, and $P_c$ is the proportion of wet cells that are expected to be in agreement by chance.

When $F$ or $\kappa$ takes the value of 1.0, it refers to a perfect agreement between two BAMs. $F$ fit measure represents the difference between two BAMs by determining the number of grid cells that same alternative has been selected by both BAMs. Thus, it represents the overall agreement of two BAMs. An $F$ value of zero indicates that there is no agreement between the two BAMs. The $\kappa$ statistic indicates the overall spatial variation of each alternative in BAM. Comparing two BAMs, $\kappa$ statistic determines the number of grid cells that the maps are in agreement about a specific alternative whether it is best or not. A $\kappa$ value of zero occurs when observed agreement is equal to chance agreement.

### 4.2 Case Study

The presented framework is demonstrated on the case study of Swannanoa River watershed located in the state of North Carolina, US. The watershed, which is a part of the larger French Broad River Basin, is located in the west North Carolina Mountains from Asheville to Montreat, the state of North Carolina. Figure 2 shows the study area along with the US states and counties. This area is selected due to its proximity to the south eastern coast of the US that exposes it to the potential path of flood-causing hurricanes and tropical storms. Communities in the Swannanoa River watershed have been severely affected through flooding by Hurricanes Francis and Ivan in 2004 including Montreat, Black Mountain, Swannanoa, and Asheville. For this study, the 33.3 km Swannanoa River reach is selected which is bounded by an area of 173.1 km$^2$, upstream of the confluence of the Swannanoa River and French Broad River, including the towns of Black Mountain, Swannanoa and city of Asheville.

## 5 Results and Discussion

In this section, the presented approach is illustrated on the Swannanoa River watershed. Required data for this framework are terrain and flow hydrographs, which are listed in Table 1. A 23 m spatial resolution DEM for the area is generated from the National Map

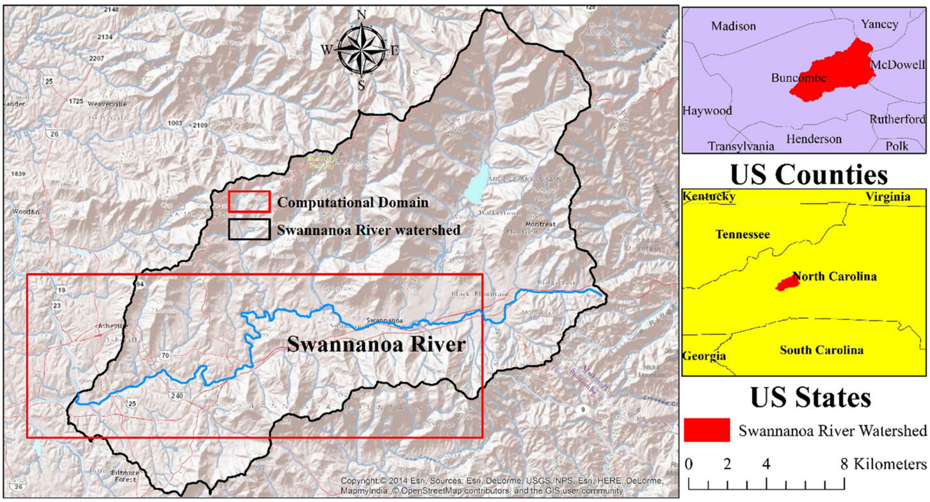



**Fig. 2** Location of the Swannanoa River watershed along with the US states and counties (Image source: ArcGIS$^{TM}$)

**Table 1** Required data, sources and resolution

| Data | Unit | Source | Resolution |
|---|---|---|---|
| Terrain | m | nationalmap.gov | 23 m |
| Flow Hydrograph | cms | USGS | 15 min |

website (http://nationalmap.gov/). This spatial resolution is selected based on Ahmadisharaf et al. (2013) suggestions for Flood2D-GPU application in the study area. The peak flow for the river is estimated by US Geological Survey (USGS) flood frequency regression functions and a generic hydrograph shape using HEC-HMS and the 100-year, 24-h SCS type II design rainfall with a depth of 155.7 mm selected from the National Oceanographic and Atmospheric Administration, Atlas 14 Precipitation–Frequency Atlas of the United States was used to create the corresponding hydrograph (Bonnin et al. 2004).

As previously presented in Fig. 1, the presented framework includes the following steps:

- Flood simulation of the alternatives: The calibrated model is run to generate rasters of flooding parameters, including depth, velocity and duration for each alternative. These results are used as inputs to the next module.
- Cell-based selection of the best alternative: The alternatives are evaluated based on the four decision attributes and the related weights using SCP. Using the MATLAB® code for SCP, which was discussed earlier, the alternatives are ranked spatially. Importance of velocity and duration of flooding is first considered as zero and then five other non-zero values are assigned to them to investigate the effects of these two parameters on BAM. By doing so, sensitivity of BAM to the criteria weights is assessed. The change in the BAM is finally explored to address the potential uncertainty in the decision making by disregarding flood velocity and duration.

## 5.1 Flood Modeling Module

Flood2D-GPU is first run for the base-case model for a 5-day flow hydrograph in 1994 August (14 to 19) with 15-min time scale. The input hydrograph is produced using an existing calibrated runoff model developed within GoldSim® Simulation Software (Lillywhite and Kalyanapu 2011). A Manning's roughness value of 0.11 (McCuen 1998) is used to represent the vegetation and light turf along the floodplain, consistent to the roughness values used in hydraulic model development by the North Carolina Floodplain Mapping Program (NCFMP) (North Carolina Floodplain Management Program NCFMP 2011). Simulated flow hydrograph is calibrated with observed flow data of Biltmore Station in the river downstream. Peak flow magnitude of 165.7 cms has been recorded on August 17 at 1:45 PM (85.8 hr after simulation start time). Comparison between the preliminary flood modeling results (Manning's value of 0.11) and the observed data showed that the model performs fairly well in terms of peak flow ($F_Q$ of 1.06) but not the time to peak ($F_T$ of 1.20). The model efficiency is thus tested with a broader range of 0.01-0.15. From this range, seven Manning's values (0.010, 0.030, 0.035, 0.040, 0.045, 0.050 and 0.15) are chosen and their efficiencies are computed. Each simulation with Flood2D-GPU with 376,832 computational grid cells takes about 30 min on a computer with an Intel Xeon DP Six Core X5690 CPU with 3.46 GHz Processor, an 8 GB Random Access Memory (RAM), NVIDIA Quadro FX5800 graphics card and Ubuntu Linux Operating System (64-bit). Fig. 3 presents the flow hydrographs in the river downstream

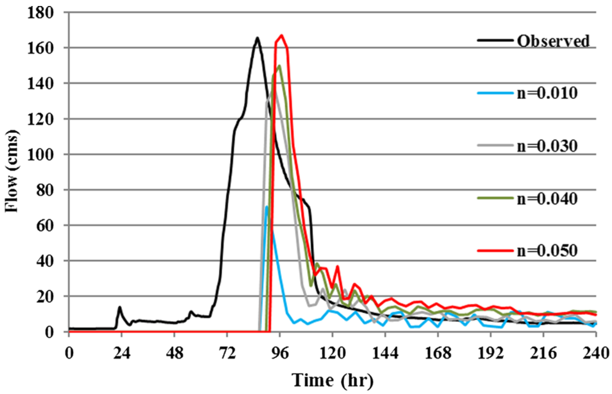



**Fig. 3** Observed and simulated hydrographs in the river downstream for some selected Manning's values

using the aforementioned Manning's values. Values of $F_Q$ and $F_T$ along with the flow hydrograph attributes, including peak flow and time to peak are presented in Table 2 and Fig. 4 for different Manning's values. The best $F_Q$ is found both at $n$=0.05 and in the range of $n$=0.11 - 0.15. However, $n$=0.05 is more efficient in terms of $F_T$. Because of this, $n$=0.05 is chosen for optimal efficiency. It is to be noted that selecting this Manning's value results in a better performance in terms of $F_Q$ than $F_T$. It gives a peak error of 1.4 cms ($F_Q$=1.01), but the performance in terms of $F_T$ is not desirable ($F_Q$=1.13). This is because of two main reasons: 1) Input data: The Swannanoa River is an ungauged watershed and there is only one flow gaging station on the river downstream. Thus, it is impossible to directly use recorded flow data from an upstream gaging station in the flood model. However, there are four rain gauge stations in the watershed. In order to produce the upstream flow hydrograph on the main river, a calibrated rainfall-runoff model was applied, which is subject to uncertainty. 2) Model limitations: Flood2D-GPU cannot incorporate lateral inflows from the subwatersheds. Thus, the overland flow from tributaries converging to the main river between upstream source point and the downstream gauge is neglected, which affects the hydrograph timing (e.g., $t_P$). It should be noted that both peak flows and time to peak are overpredicted by 0.8 % and 12.8 %, respectively, by using the selected Manning's value of 0.05.

Three hypothetical flood management alternatives are analyzed here, which are three diversion channels along with the base-case model. Location of these mitigation options are visualized in Fig. 5. For each option, the DEM is adjusted by burning the grid cells with the

**Table 2** Comparison of simulated flow parameters and observed values

| Manning's n | $Q_p$ (cms) | $F_Q$ | $t_p$ (hr) | $F_T$ |
|---|---|---|---|---|
| 0.010 | 70.2 | 0.42 | 90.0 | 1.05 |
| 0.030 | 137.6 | 0.83 | 93.3 | 1.09 |
| 0.035 | 140.6 | 0.85 | 98.3 | 1.15 |
| 0.040 | 149.8 | 0.90 | 95.3 | 1.12 |
| 0.045 | 157.9 | 0.95 | 94.8 | 1.10 |
| *0.050* | *167.0* | *1.01* | *96.8* | *1.13* |
| 0.110 | 175.7 | 1.06 | 102.8 | 1.20 |
| 0.150 | 84.1 | 0.51 | 103.0 | 1.20 |

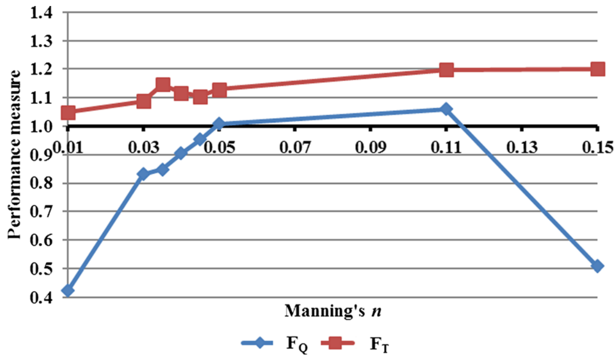



**Fig. 4** Peak flow and travel time accuracy measures

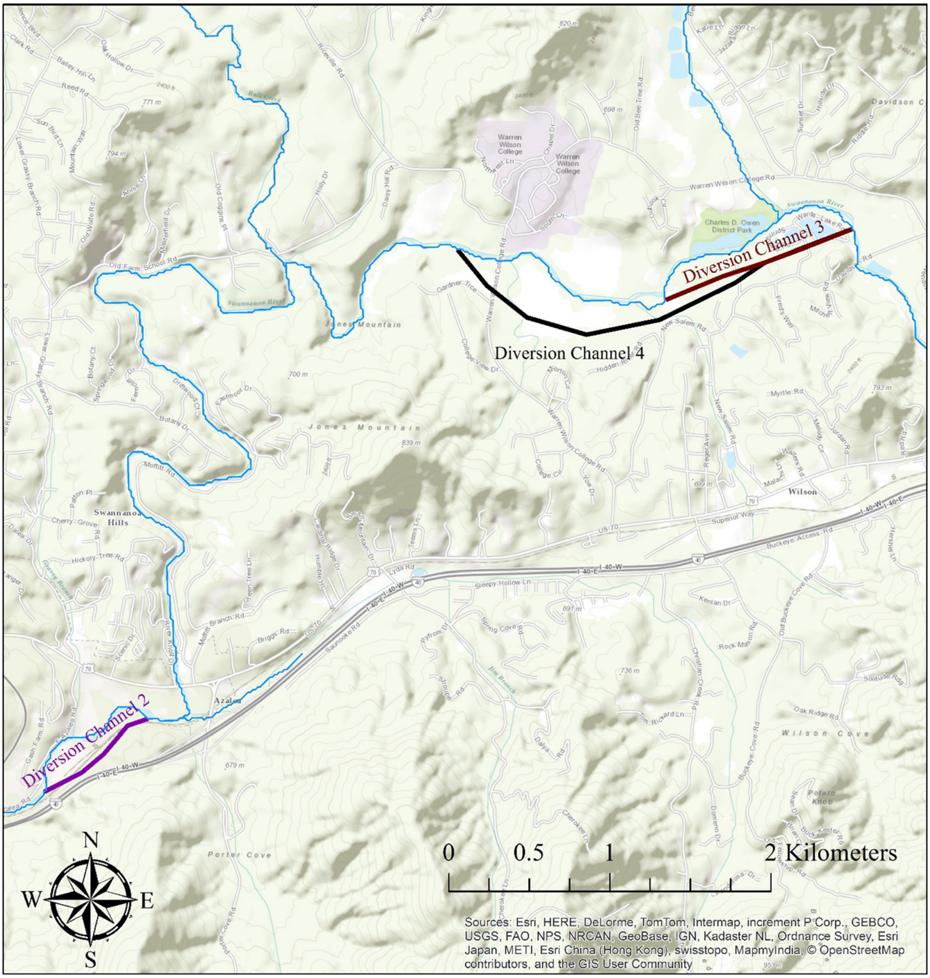



**Fig. 5** Location of the flood management alternatives

depth of the diversion channels in ArcGIS™ and 100-yr flood is simulated using Flood2D-GPU. Three model outputs, inundation depth, velocity and duration, are produced by Flood2D-GPU for each alternative. Costs of implementation for each alternative are also estimated by aggregating the costs of excavation, temporary seeding with straw and right-of-way (ROW) acquisition. The unit prices for these items are taken from the Urban Drainage and Flood Control District UDFCD (2010). As the prices belong to year 2009, a cumulative inflation rate of 10.3 % (rate for the 2009–2014 period from US Inflation Calculator (2014)) is applied to convert the rates to the present time. To generate a raster map for this criterion, the total costs of implementation are uniformly distributed on the grid cells where the diversion channel is located.

The maps of flood depth, velocity and duration of the four alternatives are compared to determine their impacts on flood parameters. In each grid cell, the minimum value of each flood parameter refers to the least possible inundation. Table 3 presents the percentage of grid cells that have the least possible inundation status by implementing an alternative. The results are presented for the wet cells (i.e., grid cells with flood depth of greater than 5 cm) and the grid cells within the streams are also excluded from the analysis to avoid biased results (Horritt and Bates 2001b). The three diversion channels perform closely in terms of reducing inundation depth. Although, diversion channels 2 and 4 overall provide slightly more improvement in terms of inundation depth compared to the diversion channel 3. However, their efficiency in terms of reducing inundation duration and velocity is very different. Diversion channel 3 reduces flood duration in only 12.4 % of the grid cells, which is much less than the other two diversion channels. Diversion channel 2 is more effective in inundation velocity reduction whereas diversion channel 4 is more effective in terms of inundation duration. Diversion channel 3, which is less effective in terms of inundation duration attenuation, is more effective in inundation velocity reduction compared to diversion channel 4, which has the best efficiency in inundation duration improvement. It is to be noted that Table 3 refers to the overall number of grid cells and does not account for spatial variability.

### 5.2 SMCDM Module

The alternatives are ranked based on six different criteria sets presented in Table 4. In the first criteria set, importance of inundation velocity and duration is set to zero. In other words, only two attributes, inundation depth and costs of implementation, are considered in the first attribute set. In the next criteria sets, five non-zero values are assigned to the weights of the inundation velocity and duration, and therefore five different four-criterion sets are implemented. Applying SCP, a BAM is produced for each weight set scenario, which are represented in Fig. 6a to f. In these maps, each grid cell indicates the best flood management alternative at that location.

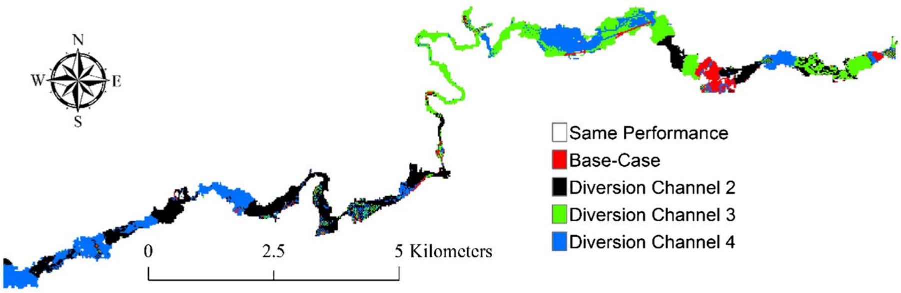
**Table 3** Percentage of the grid cells with least possible inundation by implementing an alternative

| Inundation Parameter<br>Alternative | Inundation Depth | Inundation Velocity | Inundation Duration |
|---|---|---|---|
| Base-Case | 8.0 | 16.9 | 23.8 |
| Diversion Channel 2 | 31.4 | 31.5 | 30.0 |
| Diversion Channel 3 | 29.1 | 27.0 | 12.4 |
| Diversion Channel 4 | 31.5 | 24.6 | 33.9 |

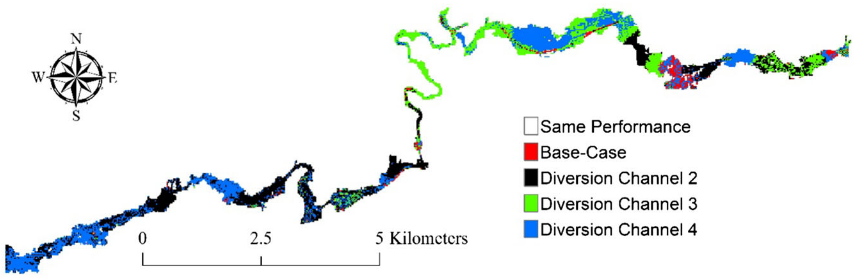
**Table 4** Criteria weight sets for different scenarios

| Criterion | Set 1 | Set 2 | Set 3 | Set 4 | Set 5 | Set 6 |
|---|---|---|---|---|---|---|
| Costs of Implementation | 0.5 | 0.4 | 0.3 | 0.25 | 0.2 | 0.1 |
| Inundation Depth | 0.5 | 0.4 | 0.3 | 0.25 | 0.2 | 0.1 |
| Inundation Velocity | 0.0 | 0.1 | 0.2 | 0.25 | 0.3 | 0.4 |
| Inundation Duration | 0.0 | 0.1 | 0.2 | 0.25 | 0.3 | 0.4 |

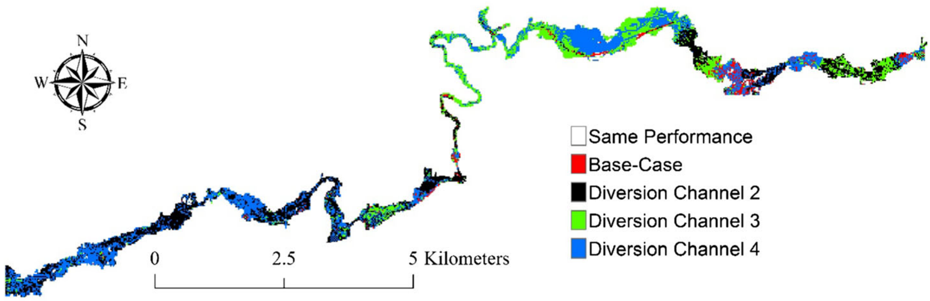
Similar to the comparison of the inundation parameters, comparison of the BAMs is also carried out within the inundation extent, and dry cells are excluded from the analysis. This is because of the fact that large portion of the case study is not flooded and therefore implementing the alternatives does not affect these locations. Thus, the results of such comparison introduce bias (Horritt 2000) and to avoid this type of biased findings, unflooded




(a)

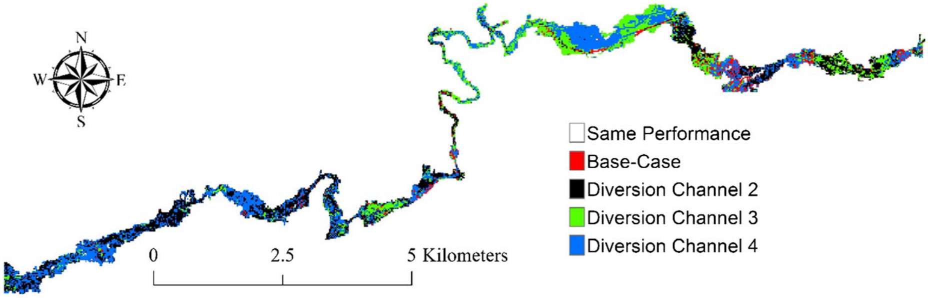



(b)

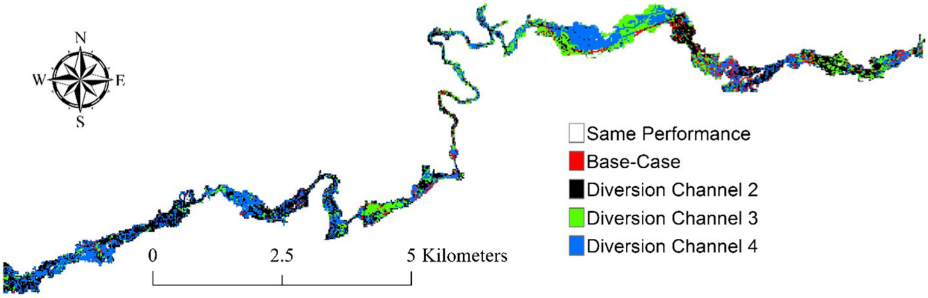



(c)

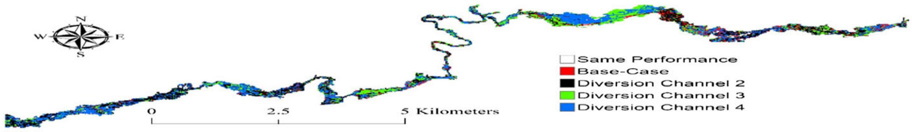
**Fig. 6** Best alternative map (BAM) for weight set: **a**) 1; **b**) 2; **c**) 3; **d**) 4; **e**) 5; and **f**) 6




(d)




(e)




(f)

**Fig. 6** (continued)

area is disregarded and the comparison is conducted within the inundation extent. Furthermore, the analysis is only performed on the floodplain and the grid cells within the streams are excluded from the analysis as they do not pose any risk. Figure 7 is a histogram plot that shows the percentage of wet cells that each alternative performs as best. It is noted that increasing the weight of inundation velocity and duration from zero (weight set 1) to 0.4 (weight set 6), leads to maximum change of 3.3 %, 1.7 %, 8.3 % and 7.8 %, respectively, in the BAM in terms of alternatives 1 to 4, respectively. By ignoring inundation velocity and duration, alternative 4 is best in 31.2 % of the wet cells within the floodplains. However, by taking these two flooding parameters into account and increasing their weight to 0.4, this number increases to 37.4 %. On the other hand, alternative 2, which possess 29.2 % of the wet cells in the weight set 1 scenario, will be the best alternative in the 21.0 % of the cells by increasing the importance of inundation velocity and duration from weight set 1 to 6.

These results are also analyzed along with the flood modeling results presented earlier in Table 3. In the first weight set, percentage of the best cells for each of the three diversion channels is very close, which is due to the fact that the efficiency of the three diversion

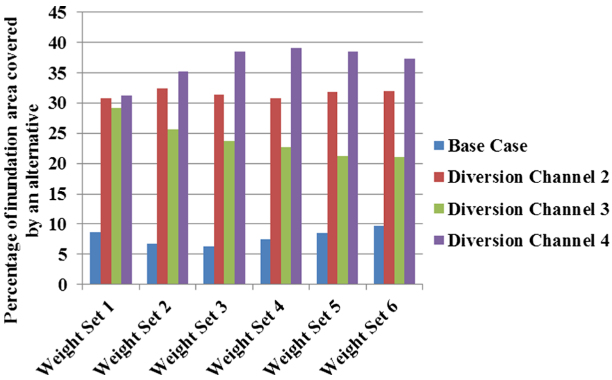



**Fig. 7** Histogram plot of best alternative in different weight sets

channels is similar in inundation depth reduction. By adding inundation duration and velocity into the decision criteria set, the difference increases. As shown in the flood modeling results, performance of the alternatives is more different in terms of inundation velocity and duration. This is the main reason for the variation in the BAMs. It is to be mentioned that the results presented through Table 3, indicate the overall percentage of the grid cells for each alternative in BAMs. In other words, they do not account for spatial variability of these grid cells. For example, if an alternative is best in 100 grid cells in a weight set and is best in 100 different cells in another weight set, it might seem that both the alternatives have same performance. However, these grid cells may not be located at the same place within the inundation extent. To overcome this limitation in the representation of the results, the difference in the BAMs are spatially explored in the next parts of the discussion.

## 5.3 Comparison Metrics

Two metrics are used to compare the results of decision making by considering inundation velocity and duration.

To compute the first agreement metrics, $F$ fit measure, BAM for the weight set 1 is spatially compared with BAMs for the five other weight sets. Total of five cell-based comparisons are performed in ArcGIS™ and an output raster is generated in each case. Each grid cell in this map is assigned with a value of zero if has same alternative as best and 1.0 if has a different alternative. The number of grid cells with the same best alternative (i.e., value of zero) presents the change in the BAM and refers to $n_{n(i \cap j)}$ parameter in Equation 7. The values of $F$ fit measure are summarized in Fig. 8. Y-axis values on the plot refer to the relative difference between weight set 1 (scenario of ignoring inundation velocity and duration) with other five weight sets (weight set 2 to 6). Based on the figure, comparing the scenario of eliminating inundation velocity and duration from the decision criteria set (weight set 1) to the others, value of $F$ decreases from 83.3 % in weight set 2, to 50.3 % in weight set 6. This indicates 17.7 % to 49.7 % change in the BAM by increasing the importance of inundation velocity and duration from 0.1 to 0.4. This remarkable change in the BAM implies a potential uncertainty in decision making by disregarding inundation velocity and duration.

The $\kappa$ measure is determined based on Equation 8 and then a relative accuracy matrix is built. For each of the four alternatives, BAM for weight set 1 is compared with each of the five other weight sets. Each comparison includes the determination of the following four quantities for each alternative (i.e., total of 16 quantifications): 1) number of cells that both two maps

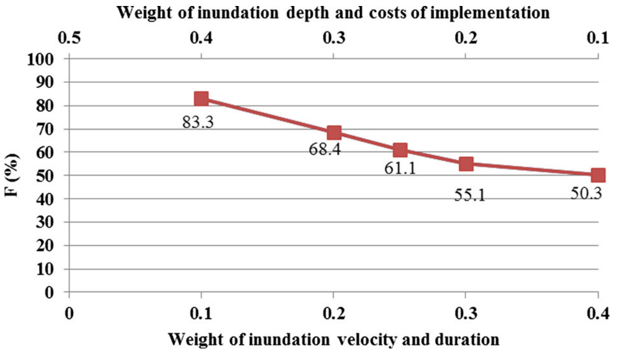



**Fig. 8** *F* fit measure values of BAMs in weight set of 2 to 5 compared to weight set 1

accept an alternative as best; 2) number of cells that first map selects an alternative as best and the other one does not; 3) number of cells that second map selects an alternative as best and the other one does not; and 4) number of cells that both two maps reject an alternative as best. Following Equation 8, $\kappa$ values are generated in each case and summarized in Fig. 9. The $\kappa$ values on the plot indicate the relative difference between weight set 1 with other five weight set scenarios (weight set 2 to 6). Based on the figure, comparing the scenario of eliminating inundation velocity and duration from criteria set (weight set 1) to others, a decreasing trend can be observed in $\kappa$ values for all the four alternatives. This variation is much smaller for base-case model compared to the three diversion channels. This means that the performance of the base-case model does not vary a lot with changing the importance of decision attributes in different weight sets. In fact, for all the three diversion channels, BAM changes drastically by consideration of inundation velocity and duration. For the base-case model, $\kappa$ varies from 92.0 % (in weight set 2) to 74 % (in weight set 6), which means by taking into account inundation velocity and duration, greater change in the BAM in terms of the base-case option is observed. For diversion channel 4, however, this variation is much greater, in which the $\kappa$ value decreases from 70.4 % (in weight set 2) to 30.1 % (in weight set 6). This is the greatest change among the other two diversion channels. For diversion channels 2 and 3, $\kappa$ value decreases from 76.6 % and 82.7 (in weight set 2) to 31.8 % and 45.7 (in weight set 6), respectively. This remarkable decrease in the $\kappa$ value for all of the three diversion channels

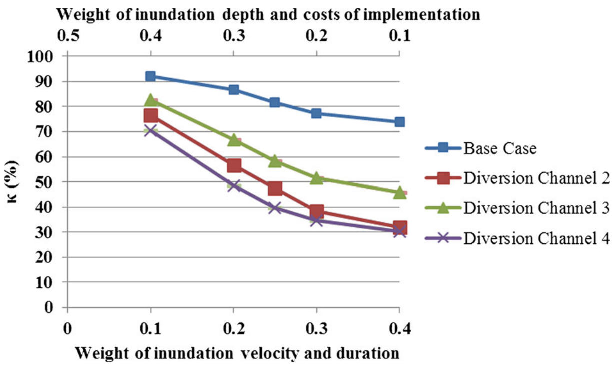



**Fig. 9** $\kappa$ values of the four alternatives in weight sets 2 to 6 compared to weight set 1

highlights the significance of inundation velocity and duration in evaluation of flood management alternatives.

The notable large change in the BAM highlights the significance of inundation velocity and duration in selection of flood management alternatives. Therefore, the investigation reveals the effects of these parameters on decision making process in current study. Disregarding them can cause a considerable change in selection of suitable flood management alternative. The analysis addresses a remarkable variation in the location of best management alternative and implies a potential uncertainty in the decision making process.

Case study results show a significant change in selection of a suitable flood management option. Although, the presented framework can be employed in other case studies due to its versatility, the results presented are case study specific. To provide general recommendations, additional studies need to be carried out to verify and/or corroborate the current findings.

Another limitation of the current study is that it only takes into account diversion channels as flood management alternative and does not consider other management approaches. A question rises that are these inundation parameters effective on selection of other flood control measures? An interesting study will be the classification of the effects of these parameters on various flood management measures. This can assist flood planners and DMs to select the most important decision parameters for different flood management measures.

Finally, the criteria weights in MCDM problems are usually determined based on stakeholders' opinions. Nonetheless, the weights were assigned arbitrarily by authors' judgments here. This was due to the study objectives for determination of importance of inundation velocity and duration. The approach aimed to address the change in the selection of flood management alternatives by taking into consideration inundation velocity and duration. For doing so, it was required to have more than a weight criteria set. Therefore, weights of these two criteria changed gradually in different weight sets and the variation in the BAM was tracked. Considering the results which indicated a remarkable alteration in the final solution, a study can be conducted together with stakeholders to validate the current findings.

## 6 Summary and Conclusions

Selection of flood management alternatives is often conducted based on inundation depth and other inundation parameters are rarely taken into consideration. A MCDM-based approach was applied in this study to investigate the impacts of inundation velocity and duration on selection of flood management alternatives. Flood2D-GPU was employed for flood modeling and SCP was applied for spatial selection of flood management alternatives. The investigation was carried out on the Swannanoa River watershed in the state of North Carolina, US. Inundation depth, velocity and duration as well as costs of implementation are taken into account as decision criteria. Four hypothetical alternatives, including three diversion channels along with the base-case model were considered as the competing alternatives. These were spatially ranked in six different weight set scenarios by using SCP and a BAM was generated in each scenario. The six weight sets were designed in a way that importance of inundation velocity and duration increases from zero to 0.4. The six weight sets were compared using $F$ fit measure and $\kappa$ statistic to investigate the impact of inundation velocity and duration on BAM. Case study results indicate up to 49.7 % change in the BAM by taking into consideration inundation velocity and duration. This high variation implies a potential uncertainty associated with the decisions made by ignoring inundation velocity and duration. The following limitations are however, existed in the current study, which are suggested for the future research:

Firstly, although the results indicate large variation in the selection of best alternative by consideration of inundation velocity and duration, a general recommendation cannot be given. Similar studies should be performed in other areas to verify the current study results. In particular, due to insufficient observed flow data in the study area and flood model limitation in incorporating the lateral flows, the calibration was not performed desirably. Although, peak flow was predicted well, time to peak was not estimated favorably, which can affect both inundation velocity and duration magnitudes. Hence, the criteria values are thus subject to uncertainty, which may affect the final BAM and the study conclusions.

Secondly, only diversion channels were taken into consideration as flood management alternatives at present study. To supplement the conclusions, other management approaches such as floodwalls and detention basins should be considered. By doing so, a more general comment about the significance of these parameters on selection of flood management measures can be recommended.

Thirdly, due to the important role of criteria weights in MCDM, weighting is done based on stakeholders and experts' opinions (Munda 2006). Nevertheless, this was out of the scope of this paper and the weights were determined based on the authors' preferences here in order to show the general procedure. Consequently, the results of this study cannot be considered as the definitive and final siting map. Weighting should be undertaken along with the specialists to incorporate their preferences and to validate the results of this study and to address the related uncertainties. This can be performed by using some interviews, questionnaires and workshops.

**Acknowledgments** The authors are grateful to the support provided by the Center of Management Utilization and Protection of Water Resources. We also acknowledge the fruitful comments by the two anonymous reviewers.

## References

Ahmadisharaf E, Bhuiyan MNM, Kalyanapu AJ (2013) Impact of spatial resolution on downstream flood hazard due to dam break events using probabilistic flood modeling. 5th Dam Saf Conf. Association of State Dam Safety Officials (ASDSO), Providence

Bana E, Costa CA, Da Silva PA, Correia FN (2004) Multicriteria evaluation of flood control measures: the case of ribeira do livramento. Water Resour Manag 18:263–283

Bonnin G, Todd D, Lin B, Parzybok T, Yekta M, Riley D (2004) Precipitation frequency atlas of the United States. NOAA Atlas 14:2

Brouwer R, Van Ek R (2004) Integrated ecological, economic and social impact assessment of alternative flood control policies in the Netherlands. Ecol Econ 50:1–21

Chen YR, Yeh CH, Yu B (2011) Integrated application of the analytic hierarchy process and the geographic information system for flood risk assessment and flood plain management in Taiwan. Nat Hazards 59:1261–1276

Citeau JM (2003) A New control concept in the Oise catchment area definition and assessment of flood compatible agricultural activities. FIG Working Week, Paris

Cohen J (1960) A coefficient of agreement for nominal scales. Educ Psychol Meas 20:37–46

Dang MN, Mukand SB, Huynh TL (2011) Evaluation of flood risk parameters in the Day river flood diversion area, Red river delta, Vietnam. Nat Hazards 56:169–194

Dutta D, Herath S, Musiake K (2003) A mathematical model for flood loss estimation. J Hydrol 277:24–49

Fernandez DS, Lutz MA (2011) Urban flood hazard zoning in Tucuman Province, Argentina, using GIS and multicriteria decision analysis. Eng Geol 111:90–98

Ferziger JH, Peric M (2002) Computational methods for fluid dynamics, 3rd edn. Springer, Berlin

Forster S, Kuhlmann B, Lindenschmidt KE, Bronstert A (2008) Assessing flood risk for a rural detention area. Nat Hazards Earth Syst Sci 8:311–322

Hajkowicz S, Collins K (2007) A review of multiple criteria analysis for water resources planning and management. Water Resour Manag 21:1553–1566

Horritt MS (2000) Calibration of a two-dimensional finite element flood flow model using satellite radar imagery. Water Resour Res 36:3279–3291
Horritt MS, Bates PD (2001a) Effects of spatial resolution on a raster based model of flood flow. J Hydrol 253: 239–249
Horritt MS, Bates PD (2001b) Predicting floodplain inundation: raster-based modelling versus the finite-element approach. Hydrol Process 15:825–842
Jonkman SN, Vrijling JK, Vrouwenvelder ACWM (2008) Methods for the estimation of loss of life due to floods: a literature review and a proposal for a new method. Nat Hazards 46:353–389
Jonkman SN, Maaskant B, Kolen B, Zethof M, Lehman W (2013) Loss of Life, Evacuation and Emergency Management: Comparison and Application to Case Studies in the USA
Jun KS, Chung ES, Kim YG, Kim Y (2013) A fuzzy multi-criteria approach to flood risk vulnerability in South Korea by considering climate change impacts. Expert Syst Appl 40:1003–1013
Kalyanapu AJ, Shankar S, Stephens A, Judi DR, Burian S (2011) Assessment of GPU computational enhancement to a 2D flood model. J Environ Model Softw 26:1009–1016
Kalyanapu AJ, Shankar S, Stephens A, Judi DR, Burian S (2012) Monte Carlo-based flood modelling framework for estimating probability weighted flood risk. J Flood Risk Manag 5:37–48
Kalyanapu AJ, Hossain AA, Kim J, Yigzaw W, Hossain F, Shum CK (2013) Toward a methodology to investigate the downstream flood hazards on the American River due to changes in probable maximum flood due to effects of artificial reservoir size and land-use/land-cover patterns. Earth Interact 17:1–24
Kalyanapu AJ, Judi DR, McPherson TN, Burian SJ (2014) Annualised risk analysis approach to recommend appropriate level of flood control: application to Swannanoa river watershed. J Flood Risk Manag. doi:10.1111/jfr3.12108
Kourgialas NN, Karatzas GP (2012) Flood management and a GIS modeling method to assess flood hazard areas-a case study. Hydrol Sci J 56:212–225
Kreibich H, Piroth K, Seifert I, Maiwald H, Kunert U, Schwartz J, Merz B, Thieken AH (2009) Is flow velocity a significant parameter in flood damage modeling? Nat Hazards Earth Syst Sci 9:1679–1992
Lee GM, Jun KS, Chung ES (2013) Integrated multi-criteria flood vulnerability approach using Fuzzy TOPSIS and Delphi technique. Nat Hazards Earth Syst Sci 13:1293–1312
Lee GM, Jun KS, Chung ES (2014) Robust spatial flood vulnerability assessment for Han River using fuzzy TOPSIS with alpha-level sets. Expert Syst Appl 41:644–654
Lee GM, Jun KS, Chung ES (2015) Group decision making approach for flood vulnerability identification with the fuzzy VIKOR method. Nat Hazards Earth Syst Sci Discuss 2:6141–6171
Levy JK (2005) Multiple criteria decision making and decision support systems for flood risk management. Stoch Environ Res Risk Assess 19:438–447
Levy JK, Hartmann J, Li KW, An Y, Asgary A (2007) Multi-criteria decision support systems for flood hazard mitigation and emergency response in urban watersheds. J Am Water Resour Assoc 43:346–358
Lillywhite J, Kalyanapu, AJ (2011) Water supply reliability assessment using Monte Carlo Simulation. 47th Annu Water Resour Conf, Albuquerque, NM
McCuen RH (1998) Hydrologic analysis and design. Prentice-Hall, Englewood Cliffs
Merz B, Kreibich H, Thieken A, Schmidtke R (2004) Estimation uncertainty of direct monetary flood damage to buildings. Nat Hazards Earth Syst Sci 4:153–163
Meyer V, Scheuer S, Haase D (2009) A multicriteria approach for flood risk mapping exemplified at the Muddle River, Germany. Nat Hazards 48:17–39
Munda G (2006) Social multi-criteria evaluation for urban sustainability policies. Land Use Policy 23:86–94
National Weather Service (NWS) (2013) Hydrologic Information Center - Flood loss data. Available at: http://www.nws.noaa.gov/hic/index.shtml. Accessed 17 September 2013
North Carolina Floodplain Management Program (NCFMP) (2011) NCFMP Program Review, Appendix B. http://www.ncfloodmaps.com/program_review.htm. Accessed 12 September 2012
Pistrika AK, Jonkman SN (2010) Damage to residential buildings due to flooding of New Orleans after hurricane Katrina. Nat Hazards 54:413–434
Qi H, Altinakar MS (2012) GIS-based decision support system for dam break flood management under uncertainty with two-dimensional numerical simulations. J Water Resour Plan Manag 138:334–341
Radmehr A, Araghinejad S (2014) Developing Strategies for Urban Flood Management of Tehran City Using SMCDM and ANN. J Computing in Civil Eng. 28 DOI: 10.1061/(ASCE)CP.1943-5487.0000360
Schröter K, Kreibich H, Vogel K, Riggelsen C, Scherbaum F, Merz B (2014) How useful are complex flood damage models? Water Resour Res 50:3378–3395
Schubert JE, Sanders BF (2012) Building treatments for urban flood inundation models and implications for predictive skill and modeling efficiency. Adv Water Resour 41:49–64
Simonovic RJ (1989) Application of water resources systems concept to the formulation of a water master plan. Water Int 14:37–50

Sinha R, Bapalu GV, Singh LK, Rath B (2008) Flood risk analysis in the Kosi River Basin, North Bihar using multi-parametric approach of Analytical Hierarchy Process (AHP). J Indian Soc Remote Sens 36:335–349
Stefanidis S, Stathis D (2013) Assessment of flood hazard based on natural and anthropogenic factors using analytic hierarchy process (AHP). Nat Hazards 68(2):569–585
Sun R, Wang X, Zhou Z, Ao X, Sun X, Song M. (2014) Study of the comprehensive risk analysis of dam-break flooding based on the numerical simulation of flood routing. Part I: model development. Nat Hazards 1–22
Tecle A, Shrestha BP, Duckstein L (1998) A multiobjective decision support system for multiresource forest management. Group Decis Negot 7:23–40
Tkach RJ, Simonovic RJ (1997) A new approach to multi-criteria decision-making in water resources. J Geogr Inf Decis Anal 1:25–44
UDFCD (2010) Cost estimator for master planning (UD-MP Cost) User Manual. Denver, CO
United Nations International Strategy for Disaster Reduction (UN-ISDR) (2013) Flood – Data and Statistics. http://www.preventionweb.net/english/hazards/statistics/?hid=62. Accessed 16 September 2013
US Inflation Calculator (2014) http://www.usinflationcalculator.com/. Accessed 5 January 2014
Willette K, Sharda R (1991) Using the analytic hierarchy process in water resources planning selection of flood control projects. Socio-Econ Plan Sci 25:103–112
Yigzaw W, Hossain F, Kalyanapu AJ (2013) Comparison of PMP-driven probable maximum floods with flood magnitudes due to increasingly urbanized catchment: the case of american river watershed. Earth Interact 17: 1–15
Yu D, Lane SN (2006) Urban fluvial flood modelling using a two-dimensional diffusion-wave treatment, part 1: mesh resolution effects. Hydrol Process 20:1541–1565
Zou Q, Zhou J, Zhou J, Song L, Guo J (2012) Comprehensive flood risk assessment based on set pair analysis-variable fuzzy sets model and fuzzy AHP. Stoch Environ Res Risk Assess 27:525–546