Evaluation of One-Dimensional and Two-Dimensional HEC-RAS Models for Flood Travel Time Prediction and Damage Assessment Using HAZUS-MH: A Case Study of Grand River, Ohio

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ABSTRACT

Even though flood damage cannot be fully controlled, its effect can be minimized to some extent by careful planning, flood mitigation measures, and an effective flood warning system. Therefore, flood warning systems with flood travel time and inundation area information, derived from accurate model prediction, can be very effective to reduce potential flood damage. While a one-dimensional (1D) model was developed in the former research for the flood warning system, there has not been many comparative assessment of model performance among 1D, two-dimensional (2D), and coupled one-dimensional and two-dimensional (coupled 1D/2D) models particularly in HEC-RAS. Therefore, this research is an extension of the prior research and was especially conducted to calculate and compare the predictive capability of 1D, 2D, and coupled 1D/2D HEC-RAS models for the computation of travel time of flood and extent of flooded area needed for a flood warning system. The research was carried out in the Grand River in Lake County, Ohio. The model performance of 1D, 2D and coupled 1D/2D models were evaluated and sensitivity analysis was conducted using the same set of flow conditions and geometric conditions. The analysis suggested that 2D model could incredibly improve the model performance compared to 1D and coupled 1D/2D models, which were evaluated through the model evaluation indicators for the observed and simulated model outputs. Additionally, sensitivity analysis of input parameters, including discharge and Manning's roughness, revealed that the 2D model was comparatively less sensitive to the changes in model inflow and Manning's roughness compared to the coupled 1D/2D and 1D models. Furthermore, the flood travel time computed using 1D model was more predicted than that of the 2D model, indicating that the 2D model would

be most appropriate to provide a safe evacuation time for the community before flood events. The 1D model consistently over predicted than that of the 2D model, which was also true for the estimation of the inundation flood zone (4.1% higher).

In addition, the appropriate assessment of flood damage in the aftermath of major flooding is crucial for flood management agencies, emergency responders, and insurance companies. Therefore, damage assessment is an important step in the evaluation of the flood mitigation measures, vulnerability analysis and flood risk mapping. This is particularly true in a context that the damage assessment so far has been primarily relying on either the coarse resolution, 30m digital elevation model (DEM), or 1D hydraulic model. As this researcher is not aware of any explicit incorporation of 2D HEC-RAS model for the damage assessment among the scientific communities, another major objective of this analysis is to outline the effects of some of the key factors including the mode of hydraulic simulation (1D vs 2D), the effect of inventory data, and the effect of topography on the flood loss estimation. This was accomplished using the 1D and 2D HEC-RAS models to produce the flood depth grids from the varying degree of topographic resolutions including 30m, 10m and LiDAR-derived DEM with and without incorporating actual field survey of the river in each case. The flood loss was estimated using Hazards United States Multi-Hazards (HAZUS-MH) loss estimation software developed by Federal Emergency Management Agency (FEMA) software, for each building within study area for flood events of various recurrence intervals from 10 to 500-year return periods. This was accomplished by updating the default-building inventory within Lake County to represent the actual building information in the model. The analysis indicated that 1D model consistently overestimated the loss in general by

61.48% for the default database and 86.12% for updated inventory. The estimation of the 1D model was consistently larger compared to the 2D model for different set of topographic resolutions and recurrence intervals. These loss estimations significantly increased when analyzed using a coarse resolution terrain, which was true regardless of selecting 1D or 2D models. Furthermore, the 2D model showed a lesser percentage increase (10.45% in 10m DEM, and 25.49% in 30m DEM), whereas the 1D model exhibited a larger increment (23.17% in 10m DEM and 76.81% in 30m DEM). This analysis suggested that the loss estimation would decrease in general by 76.21% after incorporating additional local building data into the HAZUS-MH database. More specifically, this analysis concludes that 2D model with high-resolution topographic data, including the additional incorporation of local data, in HAZUS-MH database are tremendously essential for appropriate flood damage assessment.

Keywords: Inundation, Simulation, Travel time, Inventory, Sensitivity, LiDAR, Resolutions, Models, Recurrence Intervals.

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LIST OF ABBREVIATIONS

CDMS	Comprehensive Data Management System
CFS	Cubic Feet per Second
DEM	Digital Elevation Model
FEMA	Federal Emergency Management Agency
FESWMS	Finite Element Surface Water Modelling System
FIA	Federal Insurance Administration
FIT	Flood Information Tool
GIS	Geographic Information System
HAZUS-MH	Hazards United States Multi-Hazard
HEC-FDA	Hydraulic Engineering Center Flood Reduction Analysis
HEC-FIA	Hydraulic Engineering Center Flood Impact Analysis
HEC-RAS	Hydraulic Engineering Center River Analysis System
LiDAR	Light Detection and Ranging
NAD1988	North American Vertical Datum of 1988
NED	National Elevation Dataset
NLCD	National Land Cover Database

NSE	Nash-Sutcliffe Efficiency
OGRIP	Ohio Geographically Referenced Information Program
OH	Ohio
PBIAS	Percent Bias
RMSE	Root Mean Square Error
UDF	User Defined Facility
USACE	United States Army Corps of Engineers
USACE-HEC	United States Army Corps of Engineers-Hydrologic Engineering Center
USACE-IWR	United Stated Army Corps of Engineers Institute of Water Resources
USD	United States Dollars
USGS	United States Geological Survey

Chapter 1. Introduction

Flood is one of the severe natural disaster which takes thousands of lives and affects millions of people all over the globe (Sarhadi et al., 2012). In the United States alone, there has been more than 26 major flood events from 1980 to 2016 causing an average loss of 4.3 billion dollars (Smith, 2017). Despite the significant development in tools and technique for addressing the problems related with flood hydraulics over the last few decades, the damage due to flooding has continued to rise (USGS, 2019). Meanwhile, the damage due to floods can be reduced to some extent by providing early flood information including, flood travel time and inundation areas to the public through an operative flood forecasting system.

The city of Painesville and Fairport Harbor in northeast Ohio have been frequently flooded by the Grand River over the past few years with massive flood events. The city of Painesville and nearby areas were flooded due to incessant rain events of July 2006 resulting in the declaration of a Federal and State disaster area with Disaster Declaration Number (DR-1656) in Ohio disaster history (FEMA, 2013). Significant damage of property losses of approximately thirty million dollars, including one human casualty was reported in Lake County. The damage associated with flooding can be minimized using various flood mitigation measures including flood inundation mapping and travel time computation (Lamichhane and Sharma, 2016). However, to accomplish this, the development of reliable flood model and quantification of flood damage is essential for the benefit of communities.

The development of an appropriate hydraulic model has always been a crucial step in flood analysis because the selection and application of the model depends on the various factors including the availability of the data, user's knowledge and skills, time, resources, and the overall goal of the study. For example, the selection of one-dimensional (1D), two-dimensional (2D) and coupled one-dimensional and two-dimensional (coupled 1D/2D) modelling techniques has received great attention with the advancement in flood modeling. Researchers in past evaluated a 1D HEC-RAS model with the several 2D models like LISFLOOD-FP (Dimitriadis et al., 2016; Horritt and Bates, 2002), TELEMAC 2D (Horritt and Bates, 2002; Gharbi et al., 2016), 2D FESWMS (Cook and Merwade, 2009), and 2D MIKEFLOOD (Papaioannou et al., 2016). While there are some comparative studies of 1D model with 2D and coupled 1D/2D, there are limited studies of comparing 1D or 1D/2D HEC-RAS model with the recently developed 2D HEC-RAS modeling techniques especially for the travel time prediction. Hence, the current study incorporated the dichotomy of evaluation of modeling techniques with 1D, coupled 1D/2D, and 2D modeling feature of HEC-RAS. Since 1D HEC-RAS model was already developed, this research is a continuation of the earlier work to compare and assess the predictive performance of the earlier developed 1D model with the coupled 1D/2D and 2D models for the generation of accurate travel time of flood and extent of flooded area. In addition, it is intended to upload the flood maps under flood inundation-mapping program of USGS for the potential benefit of the users and communities of Lake County, OH. Currently, the 1D HEC-RAS model and necessary files have been submitted to United States Geological Service (USGS) for review to potentially incorporate in the national portal system once the review process is completed.

Furthermore, quantifying the damage assessment after a major flood event is equally important for the planners, insurance actuaries and other stakeholders. A flood damage estimation plays a pivotal role in management of flood (Merz et al., 2010), which is typically utilized for making plans and policies (Wagenaar et al., 2016). Nevertheless, developing a flood damage estimation model is a challenging task as it is governed by the interaction of multiple factors such as hydrological components, hydraulic analysis, and others parameters (Jongman et al., 2012; Kelman and Spence, 2004). In the meantime, the availability of input data and computational resources also play a crucial role in damage assessment. Banks et al (2013) and Gutenson J. L. et al (2015) reviewed several damage assessment models employed in flood damage estimation and reported that the Hazard United States Multi-Hazard (HAZUS-MH), a damage assessment program developed by the Federal Emergency Management Agency (FEMA), to be the most promising tools for the damage assessment. A damage assessment essentially requires the development of floodwater heights during a hydraulic model and damage estimation from established depth-damage functions. While the past researchers have performed damage assessment with HAZUS-MH and with 1D hydraulic modeling techniques such as HEC-RAS for flood grids, it is still unclear how the use of more advanced 2D hydraulic modeling techniques relates to accurate damage estimation. Based on the author's review, no flood models have fully adopted FEMA’s HAZUS-MH with 2D HEC-RAS model for developing flood grids. Furthermore, the damage assessment is also influenced by the quality of the input topographic and building inventory database. Hence, the current study is intended to quantify the effect of 1D and

2D hydraulic modeling techniques, effect of topographic resolution, and building inventory data and its impact in damage assessment.

Scopes and Objectives

The damage due to flooding can be reduced with prior information of flood travel and the coverage of flooded area. The information of flood travel time, flood inundation extent, and flood damage estimation are important assets for careful planning, preparedness before the flood event, adaptation of flood mitigation measures, flood risk analysis, and early response for possible flooding in future.

The purpose of the research are listed below:

I) To perform the comprehensive evaluation of 1D, 2D and coupled 1D/2D HEC-RAS models for predicting the flood travel time and inundation area,

II) To quantify the effect of topographic data, building inventory database and the depth grid prepared in 1D and 2D HEC-RAS on the damage assessment using FEMA's HAZUS-MH model.

To accomplish the first objective, the following tasks were completed:

1) Collect input data such as geometric data and hydrologic data from the previously developed 1D HEC-RAS-model,
2) Create the terrain from the cross-section of 1D model, combine it with the floodplain terrain using the RAS-Mapper feature to create the geometric input for 2D HEC-RAS model,
3) Prepare the RAS-Mapper land use information in ArcGIS to be used in 2D model,

4) Calibrate and validate the model using field verified survey data and USGS gage station records (city of Painesvilles-04212100 and Harpersfield-04211820),
5) Compute the information of travel time of a flood event and its flooded area from HEC-RAS models,
6) Perform the sensitivity analysis of input variables: Manning’s friction coefficient and input discharge, to evaluate the models' performance.

Similarly, to accomplish the second objective the following tasks were performed:

1) Prepare the flood depth grids from 1D and 2D HEC-RAS models,
2) Prepare the building inventory data compatible to HAZUS-MH’s format using FEMA's Comprehensive Data Management System (CDMS) and ArcGIS,
3) Import the depth grids into HAZUS-MH, and user-defined facilities into the study area from the FEMA’s statewide database,
4) Run the HAZUS-MH analysis for General Building Stocks (GBS) and User-Defined Facilities (UDF) analysis,
5) Repeat HAZUS-MH analysis for different topographic resolution including 30m, 10m and 3m LiDAR DEM and for flood of different recurrence intervals.

Thesis Structure

The thesis is structured into three chapters. Chapter one describes the background, scope, objective, and thesis structure, whereas chapter two presents the evaluation of 1D, 2D, and coupled 1D/2D HEC-RAS model to compute the flood travel time and inundation maps. Chapter two also provides a detailed insight of theoretical descriptions, overall modeling approach, model inputs, study area, and calibration and validation procedure. It also incorporates sensitivity analysis, which is important in understanding the response of the model performance towards the uncertainty of the input variables. Further, this chapter also summarizes the findings in evaluating the predictive performance of different modelling techniques used especially for preparing flood inundation maps and predicting travel time.

Chapter 3 discusses the damage assessment resulting from the major flood event using FEMA's widely used HAZUS-MH tool for flood damage assessment. It includes the effect of the hydraulic modeling techniques, topographic data and inventory database in estimating the flood damage. It discusses details about updating the building database within the study area using the FEMA's techniques called CDMS. It uses the fully functional calibrated and validated 1D and 2D HEC-RAS models to generate the floodwater depth. This chapter also quantifies the estimates, provides comparative picture and concludes with the finding of HAZUS-MH analysis.

Because chapter 2 and chapter 3 have been written in journal article format, readers may find some degree of redundancy in these chapters as journal article are expected to be independent with adequate information. Chapter 2 will be submitted to Hydrological Sciences Journal as a full-length article, whereas chapter 3 will be submitted as a full-length article in different peer review journal.

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Chapter 2. Evaluation of One-Dimensional, Two-Dimensional and Coupled One and Two Dimensional HEC-RAS Models to Predict Flood Travel Time and Inundation Area for Flood Warning System

Abstract

The primary goal of this research is to evaluate the predictive capability of one-dimensional (1D), two-dimensional (2D), and coupled one-and two-dimensional (coupled 1D/2D) Hydraulic Engineering Center River Analysis System (HEC-RAS) models for the computation of the critical travel time of a flood event and its flooding extent. The research was performed in the Grand River of northeast Ohio, USA using the 1D, 2D, and coupled 1D/2D modeling features of HEC-RAS. All three hydraulic models were analyzed with the same sets of geometric conditions; that is, LiDAR data integrated with field-surveyed cross-sections, and the same set of flow conditions were used. The analysis suggested that the 2D model consistently outperformed 1D and coupled 1D/2D models as revealed by various model evaluation indicators for the simulated outcomes compared against their observed counterparts. Furthermore, sensitivity analysis indicated that coupled 1D/2D and 1D model are relatively more sensitive than the 2D model to the changes in input Manning's roughness and changes in flow. The 1D model prediction for travel time was more conservative than the 2D model, suggesting that travel time from 2D model would be more appropriate for issuing the evacuation time for a flood warning system. Similarly, the inundation area from 1D model was found to be slightly greater (4.1%) than that of 2D model.

Key words: Flooding, Inundation, Travel Time, HEC-RAS, Sensitivity.

Introduction

Flooding is one of the globally occurring natural disaster causing serious damages to infrastructures and taking thousands of lives around the world (Alho and Aaltonen, 2007; Leskens et al., 2014; Alfonso et al., 2016; Teng et al., 2017). In the United States alone, there has been more than 26 major flood events from 1980 to 2016 resulting in an average loss of 4.3 billion of dollars (Smith, 2017). The losses due to flood could be minimized by circulating timely information about flood risk to the public by the means of flood maps and flood travel time (Dutta et al., 2007). For example, flood travel time, which is the timing of the flood from the point of stream gage measurement to the affected area, can be useful for issuing early flood warnings to prevent casualties, to prevent damage, and to strengthen the perseverance of the society (Cools et al., 2006; Pappenberger et al., 2015; Carsell et al., 2004). The typical system to provide early information about the flood event (Whitehead and Ostheimer, 2009; Ostheimer, 2012; Fang Zheng et al., 2008; Krajewski et al., 2016) involves monitoring stream water levels and issuing the alerts with flood map corresponding to river water level. In this context, the inundation maps also play a prominent role in flood risk management (Porter and Demeritt, 2012; Billa et al 2011). Moreover, the flood travel time is equally important in order to announce evacuation times while issuing the flood warning. Therefore, the prediction of accurate travel time of a flood event and coverage of flooded area from a fully functional flood model is of paramount importance.

The development of a fully functional flood model requires selecting the best hydraulic model structures (1D, 2D, and coupled 1D/2D models), input parameters, and boundary conditions. Researchers have different opinions regarding the choice and selection of hydraulic models, which have been a topic of interest over the preceding years (Bates and Roob, 2000; Prestininzi et al., 2011; Papaioannou et al., 2016). The performance of 1D and 2D hydraulic models have been evaluated by various scientists (Horritt and Bates, 2002; Neal et al., 2012; Dutta et al., 2007; Gharbi et al., 2016) which have received mixed opinions. There have been some instances where 1D approach of HEC-RAS has been competent to forecast the flood coverage (M. S. Horritt and Bates, 2002). For example, M. S. Horritt and Bates (2002) and Merkuryeva et al. (2015) compared the 1D HEC-RAS model with 2D models such as TELEMAC and LISFLOOD-FP to assess their ability to predict the inundation area. They reported similar predicting capability while the differences in performance were credited to their difference in response to change in friction parameterization. However, due to the limitations of 1D model over the flow in flood plain, some researchers suggested the use of 2D models (Cook and Merwade, 2009: M. S Horritt and Bates, 2000). For example, Cook and Merwade (2009) carried out the comprehensive assessment of 1D HEC-RAS model and 2D FESWMS model, and attributed the difference in model performance to the reliability of terrain and other input data. Similarly, Gharbi et al (2016) compared 1D HEC-RAS, 1D MIKE 11 and TELEMAC 2D model and reported similar model performance, while the validity of the result was based on precision of model inputs. Papaioannou et al (2016) carried out the 1D (HEC-RAS, MIKE 11), 2D (MIKE 21, MIKE 21 FM) and coupled 1D/2D models (MIKE 11/MIKE 22) and suggested to use precise terrain datasets for flood extent analysis rather than the selection of modelling approach for accurate prediction of inundation area. Also, they conveyed a modest hint of 2D modelling techniques could be slightly better than 1D modeling. Similarly, Vozinaki et al (2017) evaluated the 1D and coupled 1D/2D HEC-RAS models, analyzed them with higher quality terrain datasets, and reported that the later model performed comparatively better.

Based on the author's review, past comparisons of 1D HEC-RAS model have been limited to other traditional hydraulic models with 2D. It has not been clear yet how the 2D HEC-RAS model would perform compared to 1D and coupled 1D/2D within HEC-RAS, especially to predict flood travel time required for timely information about flood. Thus, the primary objective of this research is to evaluate the relative predictive ability of 1D, 2D and coupled 1D/2D HEC-RAS models for accurately predicting the flood travel time and inundation area.

On the other hand, the output from hydraulic models are subjected to certain degree of uncertainties (Merwade et al., 2008) regardless of the modelling techniques, such as 1D and 2D. The uncertainties arise from model set up (Costabile and Macchione, 2015), handling of hydrological data (Bales and Wagner, 2009), and topographic and roughness data (Jung Younghun and Merwade Venkatesh, 2012). For example, Teng et al. (2017) distinguished the source of uncertainty to be stemming from model parameters (friction, conveyance parameters), model inputs (channel and flood plain geometric input) and validating data. Similarly, Abily et al. (2015) carried out the sensitivity analysis in 2D urban flood modeling and highlighted its importance to rank the uncertainty in high-resolution topographic data. Furthermore, C. H. Frey and Patil (2002) showed the role of sensitivity analysis in validating the result of a research. Therefore, secondary objective of this research is to conduct sensitivity analysis of the input variables (Manning's roughness and discharge) to detect the most sensitive model out of 1D, 2D and coupled 1D/2D.

Theoretical Description

One-Dimensional HEC-RAS Model (1D Model)

HEC-RAS, a commonly used hydraulic modeling software, was developed for analysis of 1D steady flow, unsteady flow and sediment transport by the U.S Army Corps of Engineers for (Brunner,2010). The steady flow analysis is applicable in scenarios where flow varies gradually with time and distance and are used for mapping purposes, whereas unsteady flow analysis is employed where flow and water level are rapidly varying such as in dam break flood waves, flash floods, levee overtopping, and breaching (Brunner, 2010). Unsteady flow routing solves the 1D Saint-Venant equation that is comprised of a continuity and momentum equation (1) and (2), respectively, are listed as below:

$$\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial x} = 0 \tag{1}$$

$$\frac{\partial Q}{\partial t} + \frac{\partial\left(\frac{Q^2}{A}\right)}{\partial x} + gA\frac{\partial H}{\partial x} + gA\left(S_0 - S_f\right) = 0 \tag{2}$$

where, A represents cross-section area; t is time, Q is water-flow; x is the measured distance in the direction of the channel; g is the gravitational acceleration; H is the height of water level above the datum; S_0 is the slope of the river bed and S_f is energy slope.

A four-point implicit finite difference technique is utilized for solving the 1D unsteady flow equation under which space derivatives and function values are evaluated at interior points (Brunner, 2010).

Similarly, 1D steady flow (Brunner, 2010) solves the energy equation by an iterative standard step method between the two successive cross sections to compute the water surface elevation for slowly varying water profiles . The energy equation between the consecutive sections is shown in equation (3) as below:

$$Z_1 + Y_1 + \frac{\alpha_1 V_1^2}{2g} = Z_2 + Y_2 + \frac{\alpha_2 V_2^2}{2g} + h_e \quad (3)$$

Where Z_1 refers the elevation at section 1, Z_2 refers the elevations at section 2,

Y_1 and Y_2 are height of water at section 1 and section 2 respectively,

α_1 *and* α_2 are velocity weighting coefficients at section 1 and section 2 respectively,

g = gravitational acceleration,

h_e = energy loss between upstream and downstream cross-sections.

Two-Dimensional HEC-RAS Model (2D Model)

The two-dimensional flowing pattern of flood waves has encouraged the use of 2D hydraulic models for mapping the flood (Horritt and Bates, 2002). The recent HEC-RAS's unsteady flow analysis from version 5.0 onwards includes the capability to perform 2D flood modeling (Brunner, 2016). The 2D model either uses the full Saint-Venant equation or uses the diffusion wave equation. The 2D Saint-Venant equation solves the problems with greater computational efficiency requirement, whereas the 2D diffusion wave equation solves the problems with faster and higher stability. The time step for running the model is governed by the Courant condition (equation 4) for the Saint-Venant equation (full momentum) and (equation 5) for diffusion wave equation (Brunner, 2016).

$$C = \frac{V\Delta T}{\Delta X} \leq 1.0 \text{ (with a max } C = 3.0) \quad (4)$$

$C = \frac{V\Delta T}{\Delta X} \leq 2.0$ (with a max C = 5.0) (5)

where C is Courant Number, V is flood wave velocity, ΔT is computational time step and ΔX is the average cell size.

The basic concept of this model is to discretize the river and the flood plain into individual 2D cells. The 2D model takes a sub-grid bathymetry approach (Casulli, 2008), that extracts the hydraulic and geometric property table, to represent the cell and cell faces, from the sub-grid terrain. The 2D feature of HEC-RAS pre-processes each cells to create the detailed property table. For instance, if a model is built with computational grid cell size of 50x50 ft. with detailed terrain of 3x3 ft. resolution, the 2D model pre-processes to calculate the relationship between elevation and volume based on the detailed terrain within each cells. Similarly, the detailed relationship of area, wetted perimeters and roughness with elevation is also established for each grid cell.

The unsteady flow equations in 2D models utilizes implicit finite volume algorithm. This algorithm allows bigger time intervals compared to the explicit method, making the model more stable and robust regarding traditional finite element techniques (Brunner, 2016). The unsteady flow routing solves the continuity and momentum equation in space and time, which are presented in the following equations.

$$\frac{\partial H}{\partial t} + \frac{\partial (hu)}{\partial x} + \frac{\partial (hv)}{\partial y} + q = 0 \tag{6}$$

$$\frac{\partial u}{\partial t} + \frac{u\partial u}{\partial x} + \frac{v\partial u}{\partial y} = -g\frac{\partial H}{\partial x} + v_t\left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}\right) - c_f.u + fv \tag{7}$$

$$\frac{\partial v}{\partial t} + \frac{u\partial v}{\partial x} + \frac{v\partial v}{\partial y} = -g\frac{\partial H}{\partial y} + v_t\left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2}\right) - c_f.v + fu \tag{8}$$

Where t is time, u is velocity component in x-direction, v is velocity component in y directions, h(x,y,t) is height of water, H is total head, and q is the flux term's source, g is gravitational acceleration, v_t is horizontal eddy velocity, c_f is the bottom friction coefficient, f represent Coriolis coefficient, and R is the hydraulic radius. The left side of the equation has terms representing acceleration, while the right side of the equations has terms representing forces (internal and/or external) affecting the fluid. The program's documentation manual (USACE, 2016) provides additional information on HEC-RAS's theoretical background.

Coupled One-/Two-Dimensional HEC-RAS Model (Coupled 1D/2D Model)

The 2D model has the ability to run all three modes of simulation including 1D, 2D and coupled 1D/2D modelling using a unsteady flow analysis. The coupled model allows users to work in large river system involving 1D modeling for river system with dominant unidirectional flow and 2D model for wider flood plain, which requires higher level of hydrodynamic precision. The 2D areas can be connected to 1D model directly as upstream end or downstream end or using lateral structure (Brunner, 2016). Based on the time intervals, a strong connection between the 1D and 2D model solutions (Brunner et al, 2015) with an option to repeat the calculation back and forth between 1D and 2D flow elements to calculate the water surface elevation.

Nominal Range Sensitivity Analysis Method

The nominal range sensitivity method or local sensitivity analysis uses a probabilistic approach that filters vital inputs in the model (Frey and Patil, 2002). This analysis evaluates the effects of model output observed by varying the particular input through its whole range of possible values (Cullen and Frey, 1999). Any variation in the results due to variation in input variable is called model sensitivity or also referred as swing weight for the specific input within a model (Morgan and Henrion, 1990) which can be measured as either positive or negative percentage change(Frey et al, 2003). The following equation (9) is used to compute the sensitivity index.

$$\text{Sensitivity} = \frac{\text{Output}_{\text{max input}} - \text{Output}_{\text{min input}}}{\text{Output}_{\text{nominal input}}} \tag{9}$$

While various sensitivity analysis approaches are presented in the literatures (Frey and Patil, 2002), a local, nominal range sensitivity method has been widely used for simplicity. For example, Delenne et al (2012) used local sensitivity analysis to perform uncertainty analysis to identify the risks of dam failure and river flooding. They found out that the local sensitivity analysis, which requires simpler computational efforts, can be successfully applied in place of a computationally demanding global method involving thousands of simulations in complex flow problems with the same flow. Similarly, this sensitivity analysis has been successfully applied in hydraulic modeling to study the uncertainty in a model (Wohl Ellen E, 1998 and Tsubaki and Kawahara, 2013). This method is especially useful when users are interested to evaluate the model output by changing particular model input at a time, while the base value of the remaining inputs constant (Cullen and Frey, 1999). The uncertainty of the flood inundation is originated mainly from the channel and floodplain Manning's roughness, input discharge (Dimitriadis et al., 2016; Bozzi et al., 2015; Jung Younghun and Merwade Venkatesh, 2012), model calibration, and boundary conditions (Hall J. W. et al., 2005) etc.

Materials and Methodology

Study Area

The research is conducted in the Grand River watershed in northeast Ohio (Figure 2-1). The watershed extends spatially from latitude 41° 50’ N to 41° 17’ N and longitude 81° 19’ W to 80° 36’ W covering five counties of northern Ohio, namely Ashtabula, Lake, Geauga, Portage and Trumbull Counties. It has a length of about 103 miles, catchment area of 705 square miles, and elevation ranging from 564 ft. to 1309 ft. The river section modeled in this study is 32 miles extending from Harpersfield to Fairport Harbor and consists of three major tributaries including Big creek, Paine creek and Mill creek. The USGS gage station is located at Harpersfield and Painesville.

The City of Painesville has been flooded by disastrous flood events over the past years in 2006, 2008, 2011 and 2013. The meandering river close to the city of Painesville has some urbanized area with commercial and residential buildings within the flood extent, which is susceptible to high flood damage. The city of Painesville was severely damaged by disastrous flood of nearly 500-year return period in July 2006 following incessant rainfall of more than 11 inches. This incurred an estimated damage of $30 million and one fatality (Ebner et al., 2007). More than 600 people were evacuated during this catastrophic flood, which not only damaged more than 912 homes and business, but also destroyed 5 bridges and closed 13 roads (Ebner et al., 2007). During this event, the Lake county , Geauga county, and Ashtabula county were announced as disaster area with Disaster Declararion Number (DR-1656) in Ohio disaster history (FEMA, 2013).

Overall Modelling Approach

The 1D, 2D and coupled 1D/2D models (Figure 2-2) were compared by setting all three models to the same set of geometric and boundary conditions. The 1D model assumes all water flow in a longitudinal direction, models terrain as a series of river cross-sections, and simulates an average velocity and water surface elevations at individual cross section. While the 2D model allows water flow considering the flow along (longitudinal direction) and across (transverse direction) the river sections, represent terrain a continuous grid cells, and simulates the continuous distribution of velocity and water surface throughout the grid. In this analysis, the 1D model was developed by importing the input data after preprocessing from HEC-GeoRAS. The pre-processing in HEC-GeoRAS, an ArcGIS extension, is carried out to prepare input geometry data. The flood analysis is conducted in HEC-RAS and its result are post-processed to create inundation maps. The unsteady model was adopted to calibrate the input parameter and to validate HEC-RAS model using the flow data from 1996 to 1998, which was downloaded from two USGS gage stations. The model parameters were calibrated and the same calibrated model were utilized for simulating 2006 flood events to calculate the travel time of flood and to generate flood maps in steady state scenarios. Steady state velocity profile was used to compute the flood travel time between the consecutive cross sections, and to create the flood maps by post-processing the results with HEC-GeoRAS.

The 2D model was developed using terrain formed by LiDAR data and field verified cross-sections. The geometric data for representing the river was same for both 1D and 2D models. Similarly, the computational mesh size of 50ft x 50ft was chosen due to reasonable computational time. Since the 2D model does not require additional post-processing outside the software, mapping of inundation area and calculation of travel time was accomplished in RAS-Mapper within the 2D model itself. The calibration and validation of the models were accomplished with same set of input flow data for all models. The coupled 1D/2D model was developed by connecting the upstream 1D riverine model (12 miles of river), where river is relatively narrow with the downstream 2D flow area to represent the flood plain (20.2 miles of river). It was expected that combined modeling approach would help to get the reasonable trade-off amid the accuracy of the flood model and the efforts required for its computation.

HEC-RAS Model Inputs

Elevation Data

The elevation dataset required to build the model was the high-resolution LiDAR data obtained from Ohio Geographically Referenced Information Program (ORGIP) portal. The use of highly accurate, LiDAR is advantageous in creating accurate inundation maps (Cook and Merwade, 2008). The 1D model input features such as cross sections and geometric features (bridges, culverts, etc.) were generated from HEC-GeoRAS using LiDAR dataset. Even though LiDAR can accurately represent the terrain, it cannot appropriately characterize the channel bathymetry. It is mainly because LiDAR waves cannot penetrate into subsurface terrain along river leading inaccuracies in modeling (Podhoranyi and Fedorcak, 2014). Thus, to incorporate the true river geometry in flood analysis, a field survey was carried out at 77 cross-sections. The various river cross-sections were generated by interpolating the field verified cross-sections.

For the 2D model, terrain from LiDAR data and cross-section interpolation surface were combined to form a single terrain (Figure 2-3) in RAS-mapper to include actual terrain underneath the water surface in the channel.

Land use Data

The land cover dataset were extracted from National Land Cover Dataset (NLCD, 2011). The river basin has 41.81% of forest, 24.54% cultivated, 10.31% developed, 9.258% hay/pasture, 7.67% water/wetland, 4.19% emergent herbaceous, 2.12% Shrub/scrub and 0.08% barren land area as shown in Figure 2-4. The Manning's roughness value for the 2D model was used based on the each land use characteristic.

Flow and Boundary Conditions

The flow data required for the boundary condition for 1D and 2D models were obtained from USGS at Harpersfield (04211820) and Painesville Stations (04212100). The flow hydrographs were used at upstream section at Harpersfield, whereas the flow values at ungagged tributaries (Mill Creek, Paine Creek and Big Creek) were computed as the percentage contribution of catchment area using catchment area method as discussed in Whitehead and Ostheimer (2009). The downstream condition was used as a normal depth using the average slope of channel at the downstream station.

Model Evaluation Criteria

Four statistical indicators, namely Nash-Sutcliffe Efficiency (NSE), coefficient of determination (R^2), and Root Mean Square Error (RMSE) to standard deviation (RSR) and percentage Bias (PBIAS), were utilized to ensure the agreement between the modeled and the observed values. The main goal is to reduce the error while comparing the modeled outcomes with their observed counterparts.

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n} \left(Y_i^{obs} - Y_i^{sim} \right)^2}{\sum_{i=1}^{n} \left(Y_i^{obs} - Y_{obs}^{mean} \right)^2} \right] \tag{10}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n} \left(Y_i{}^{obs} - Y_{obs}^{mean} \right) \left(Y_i{}^{sim} - Y_{sim}^{mean} \right)}{\left[\sum_{i=1}^{n} \left(Y_i{}^{obs} - Y_{obs}^{mean} \right)^2 \sum_{i=1}^{n} \left(Y_i{}^{sim} - Y_{sim}^{mean} \right)^2 \right]^{0.5}} \right)^2 \tag{11}$$

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\sum_{i=1}^{n} \left(Y_i^{obs} - Y_i^{sim} \right)^2}}{\sqrt{\sum_{i=1}^{n} \left(Y_i^{obs} - Y_{obs}^{mean} \right)^2}} \tag{12}$$

$$PBIAS = \left[\frac{\sum_{i=1}^{n} \left(Y_i{}^{obs} - Y_i{}^{sim} \right) X\ 100}{\sum_{i=1}^{n} \left(Y_i{}^{obs} \right)} \right] \tag{13}$$

where Y_i^{obs} is the ith value in observed value, Y_i^{sim} is the ith value of modeled data, Y_{obs}^{mean} is the average value of observed value, Y_{sim}^{mean} is the average of modeled data, and n represents total observations number.

NSE is a measure model quality in the form of representation of variance (Nash and Sutcliffe, 1970). The NSE shows the degree of fit in 1:1 line. The range of NSE lies from -∞ to 1, where value of 1 shows the best fit and the values between 0.5 and 1 indicates the acceptable level of performance (Moriasi et al., 2015).

The determination coefficient (R^2) represent the collinear relationship between the simulated output and observed values (Moriasi et al., 2015). The value R^2 lies from zero to one showing the proportion of variance in measured data. The value close to greater than 0.5 is considered acceptable, whereas the value close to one indicates the perfect model.

The RSR, which is the ratio of RMSE to standard deviation, shows residual model error where values closer of zero is optimal condition showing least RMSE with least residual variation. Better model prediction is characterized by the lower values of RSR.

PBIAS shows the trend of the modeled output data being higher or lower than the observed value (Gupta et al., 1999). The lower value of PBAIS (close to zero) shows the better model performance with best value being zero. The PBIAS value greater than zero shows underestimation, whereas value less than zero shows the overestimation of the observed counterparts (Gupta et al., 1999).

Model Calibration and Validation

All three hydraulic models were calibrated to get an optimum Manning's coefficient by relating the model predicted flood stage and flood flow values with the observed counterparts. The initial trial values of friction coefficient were selected based upon the visual inspection of the channel at several locations and review of the existing literatures. For example, M. S. Horritt and Bates (2000) showed that the Manning's coefficient for the main channel roughness ranged from 0.01 to 0.05 and for flood plain it ranged from 0.01 to 0.02. Chow et al (1998) provided the working range of friction coefficient between 0.035 to 0.065 for river section and between 0.08 to 0.15 for overflow area. Similarly, Brunner (2016) and Arcement and Schneider (1989) provided the suggested range of roughness values for 2D model. In order to make the calibration parameter tractable, single friction value for river section and flood plain was adopted for 1D model. Each of the hydraulic models was calibrated and validated using series of flood scenarios that were measured between 1996 to 1998 for different sets of Manning's values. The optimum roughness valued obtained from the calibration were used later on to create the flood maps and calculate the travel time from each model.

Sensitivity Analysis for Model Evaluation

Most of the hydraulic models need to be calibrated due to uncertainty involved in model structures and available data (Dottori et al., 2013). The calibration of a HEC-RAS model is particularly sensitive to a Manning's roughness (Parhi, 2012). In this study, sensitivity analysis for two input variables, Manning's roughness and input discharge, were carried out for all models. The sensitivity of Manning's roughness and input discharge were conducted varying one parameter at a time.

Result and Discussion

Simulation of Hydraulic Model

The performance of 1D, 2D and coupled 1D/2D models were evaluated using various statistical indicators. The statistical indicators measuring the performance of the model were above the suggested values (NSE > 0.5, PBAIS $\pm$ 25% and RSR ≤ 0.7) as suggested by Moraisi et al. (2015). The results of all three hydraulic models for stage calibration/validation at Harpersfield gage station is reported in Table 2-1. Likewise, the results of flow calibration and validation at Painesville gage station is shown in Table 2-2. Similarly, the comparison of simulated water level with its observed counterpart at upstream gage station from 1D, 2D and coupled 1D/2D models is visualized with graphs presented in Figure 2-5. In the same way, Figure 2-6 presented the graphical plot of observed and simulated flow rate measured at downstream gage station using 1D, 2D, and coupled 1D/2D models. The graphical plot shows that the 2D model is consistently performing better in calibration, which is further confirmed by the statistical model evaluation indicators. Additionally, the graphical plot of a model validation is shown in Figure 2-7. The analysis in terms of statistical indicators and graphical comparison suggested that 2D model exhibited improved performance compared to 1D and coupled

1D/2D models. Even though coupled 1D/2D model are found to be improving the model accuracy (Vozinaki et al., 2017), this analysis showed only the modest improvement in terms of percent bias, especially for discharge calibration. In fact, this study did not detect significant improvement of the model performance in coupled 1D/2D model compared to 1D model which is in agreement with the Papaioannou et al. (2016). They conducted a study to compare 1D, 2D with coupled 1D/2D in Mike 11/Mike 21 model and reported that the accuracy of input data is more crucial compared to model structure. Regardless, 2D model is found to be better in urban flood modeling after successful model calibration (Mignot et al., 2006; Ernst et al., 2010). In this study, 2D model demonstrated better result than coupled 1D/2D and 1D model in model evaluations, which was also revealed by sensitivity analysis indicating 2D model was less sensitive to the input parameters.

Travel Time Comparison

Flood travel time was calculated from Harpersfield station to the City of Painesville and to the Fairport Harbor during major flooding events of 2006, 2008 and 2011. Since a single velocity for entire cross section in 1D model represented the flow, we computed the travel time using this velocity and the length between the two adjacent river cross sections. However, the velocity is expected to vary across the longitudinal and transverse direction of river. As a result, this might not predict the appropriate flood travel time while using a single velocity value in 1D model. Since 2D model can effectively represent the velocity variation across the cross sections, the travel time was also computed using 2D model. It is worthwhile to report that 2D unsteady model computes different velocity in longitudinal and transverse direction as velocity is anticipated to vary at each locations of the channel. In fact, each quartile ranges of velocity variation and longitudinal distance between the cross sections were measured to compute the travel time between these sections. The various ranges of velocity profile from 2D model and peak velocity from 1D model is presented in Figure 2-8. The travel time for flood wave from Harpersfield to the city of Painesville for 1D model were found to be 4.37hr, 5.48hr, and 5.49hr for 2006, 2008 and 2011 flood, respectively, whereas corresponding travel time using 2D model were 3.66hr, 4.55hr and 4.46hr, respectively. Presumably, the travel time predicted from 1D model, which computed the average velocity for each cross-section, ranged somewhere between the quartile ranges of 2D model. In this analysis, travel times from coupled 1D/2D model were not calculated as coupled model did not show significant improvement over 1D model. More importantly, travel time of 1D model were within the range of 2D models, and hence possibility of getting different results from coupled 1D/2D model was not expected. Crucially, the 2D model predicted more conservative (less) travel time than was predicted from 1D model, which could be more beneficial for the early warning system from the perspective of safety and protection.

Inundation Area comparison

The major flood event of 2006 and 2008 were used to compute the inundation area and generate flood maps using calibrated and validated 1D and 2D models. Area calculations from coupled 1D/2D model was not performed as it could not exhibit improved performance in calibration. Further, the sensitivity analysis of the coupled 1D/2D model was also not different from the 1D model. Results from 1D HEC-RAS model were post-processed in HEC-GeoRAS to create the inundation map, whereas 2D model had its advantage of RAS-mapper feature for result post-processing. The flooded area predicted from 1D model was 4.33 sq. miles and 3.45 sq. miles, whereas the predicted inundation area from 2D model was 4.19 sq. miles and 3.24 sq. miles for 2006 and 2008 flood, respectively as reported in Figure 2-9. The geographical exposure (Figure 2-10) of the inundation maps overlaid with google map showed that larger inundation areas were predicted from 1D model. This was not surprising as the 2D model was better calibrated and validated (as explained in model calibration and validation), and showed least sensitivity to change in input parameter, which will be discussed in the next section. The better performance of 2D model in inundation area prediction was also detected by Cook and Merwede (2009), where they recommended the use of more detailed 2D model for developing more accurate and realistic estimation of the inundation area.

Sensitivity Analysis

Manning's Roughness

To perform the sensitivity analysis, Manning's friction factor was varied from -40% to +100% of the best-calibrated nominal or base value. The base value of friction coefficient for 1D model was 0.035 for river channel, which was varied from 0.0035 to 0.07. The model simulation was performed at each 10% increment from -40% to +100%, during which stage and discharge were measured at upstream and downstream stations, respectively. Similarly, the base Manning's roughness value from calibration were found to be 0.045 and 0.022 for coupled 1D/2D and 2D models, respectively, which were varied at same percentage increment during each simulation. The output results from the HEC-RAS models including stage and discharge were measured at corresponding stations. The

1D simulation analysis were not successful for all Manning's roughness value, especially when the roughness value was decreased in the range from -90% to -60%, due to model instability, whereas the coupled 1D/2D and the 2D model were operational in all ranges of Manning's roughness value. The graphical result of sensitivity analysis (Figure 2-11) shows that both the outputs (stage and output flow rate) from the 1D and the coupled 1D/2D models' prediction are more sensitive than from the 2D model. The statistical calculations (Table 2-3) shows that 1D and coupled 1D/2D model exhibited higher standard deviations of simulated stage and discharge compared to 2D model. The consistently higher standard deviation for the same mean values of stage and discharge suggested that 1D and coupled 1D/2D models are relatively more sensitive to the friction coefficient compared to 2D model, which is also supported by the sensitivity index of corresponding models (Table 2-3). The analysis from graphical and statistical computations suggested that 1D and coupled 1D/2D models are more sensitive than 2D model. This result is similar to previous finding (Dimitriadis et al., 2016), where they reported that 1D HEC-RAS exhibited larger sensitivity to the change of channel roughness compared to 2D model such as LISFLOOD and FlO-2D.

Sensitivity with Input Discharge

The base discharge value needed for sensitivity analysis was selected from the flood event of 4/10/1998 to 4/30/1998, which exhibited the best fit between the observed and simulated value for both 1D, coupled 1D/2D, and 2D models. The base value was varied from -50% to +100% of the selected nominal value (7250 cfs). The simulation was run for each hydraulic model at every 10% increment of base value ranging from 1450 cfs to 14500 cfs while remaining parameters were constant. For each of the model execution, modeled stage and discharge were recorded at upstream and downstream stations, respectively. The graphical result of sensitivity analysis of input discharge (Figure 2-12) showed that the output stage for 1D and coupled 1D/2D model were more sensitive than 2D model. This result is also supported by the statistical comparison (Table 2-3) including the standard deviation and sensitivity index of simulated stage from each of model. However, the effect on output discharge were strikingly similar for 1D, coupled 1D/2D and 2D models indicating that the 1D and coupled 1D/2D models were no longer more sensitive than 2D model while considering the effect of output discharge.

Conclusion

Flood inundation information are crucial to provide reliable information to public for flood risks analysis, planners, insurance companies, and other stakeholders. Calculation of flood travel time and prediction of extent of flooded area are essential for flood warning system to issue evacuation time for the protection of lives and property. However, the computation of these parameters are subjected to the quality of the topographic data, geometric configuration, input parameters, and the selection of hydraulic model structure. While there has been significant progress in the flood modeling, the selection of the 1D, the 2D and the coupled 1D/2D models have not been explored considerably within HEC-RAS itself, especially for predictive capability in terms of flood wave travel time and inundation area. Therefore, the principal objective of this study is to compare the ability of hydraulic models to predict the flood wave travel time and inundation area using the 1D, the 2D and the coupled 1D/2D features of HEC-RAS. All three models were set up with the same topographical data and same boundary conditions for the flow and the stage. These hydraulic models were calibrated to optimum

Manning's roughness value to ensure the optimal fit between the modeled result and observed values. The modeled results from all three models were considerable agreement with their measured counterparts. The statistical indicators did not show any significant evidence that the coupled model was better than the 1D model. However, the 2D model exhibited better performance than coupled 1D/2D and 1D models measured with respect to the statistical indicators as well as graphical comparison.

From the sensitivity analysis of these hydraulic models with 40 simulations, the 1D and the coupled 1D/2D models were found to be more sensitive than 2D model to the variation in input Manning's roughness as well as to the input discharge. This was analyzed from the graphical comparison as well as and statistical indicators. Modeling a floodplain with the 2D feature and main river channel with the 1D feature is a common practice in a coupled model because of considerable reduction of the computational cost and simulation time. However, coupling between the model components could also be responsible for carrying over model uncertainty making it more sensitive to input parameters.

Furthermore, the flood travel time predicted from 2D model was shorter than from 1D model making the 2D model a more conservative prediction for travel time estimation. Furthermore, the 2D model predicted smaller inundation area compared to 1D model. Even though, the 1D model had the advantage of shorter computational time (2-4 minutes) compared with computational time for 2D model (1 to 10 hours), the better accuracy was exhibited using 2D model. Additionally, it is safe to decide based on worst possible condition, and hence smaller travel time predicted from the 2D model will be reasonable for planning early evacuations and possible flood hazards. Moreover, there may be other factors contributing uncertainties in prediction of flood travel time and flooded area, which should be investigated in depth with global sensitivity techniques along with the use of probabilistic approaches for accounting the uncertainties while using hydraulic models in flood warning and flood mitigation measures.

Nevertheless, it is cardinal to treat the result with great caution because the extension of this approach over other study area for different flood events may exhibit different behavior. The assumption of single valued friction coefficient used in the calibration/validation of this model could not always describe the channel and floodplains property. Furthermore, the flow/discharge value at the ungagged creeks provided by catchment area ratio method may not always be the true representation of the flow condition during the flood events. Regardless, this research concludes that application of a 2D model is preferred than coupled 1D/2D or 1D model for travel time and flooded area prediction, which are essential for safe evacuation of the people while issuing the flood warning system.

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Figures and Tables:

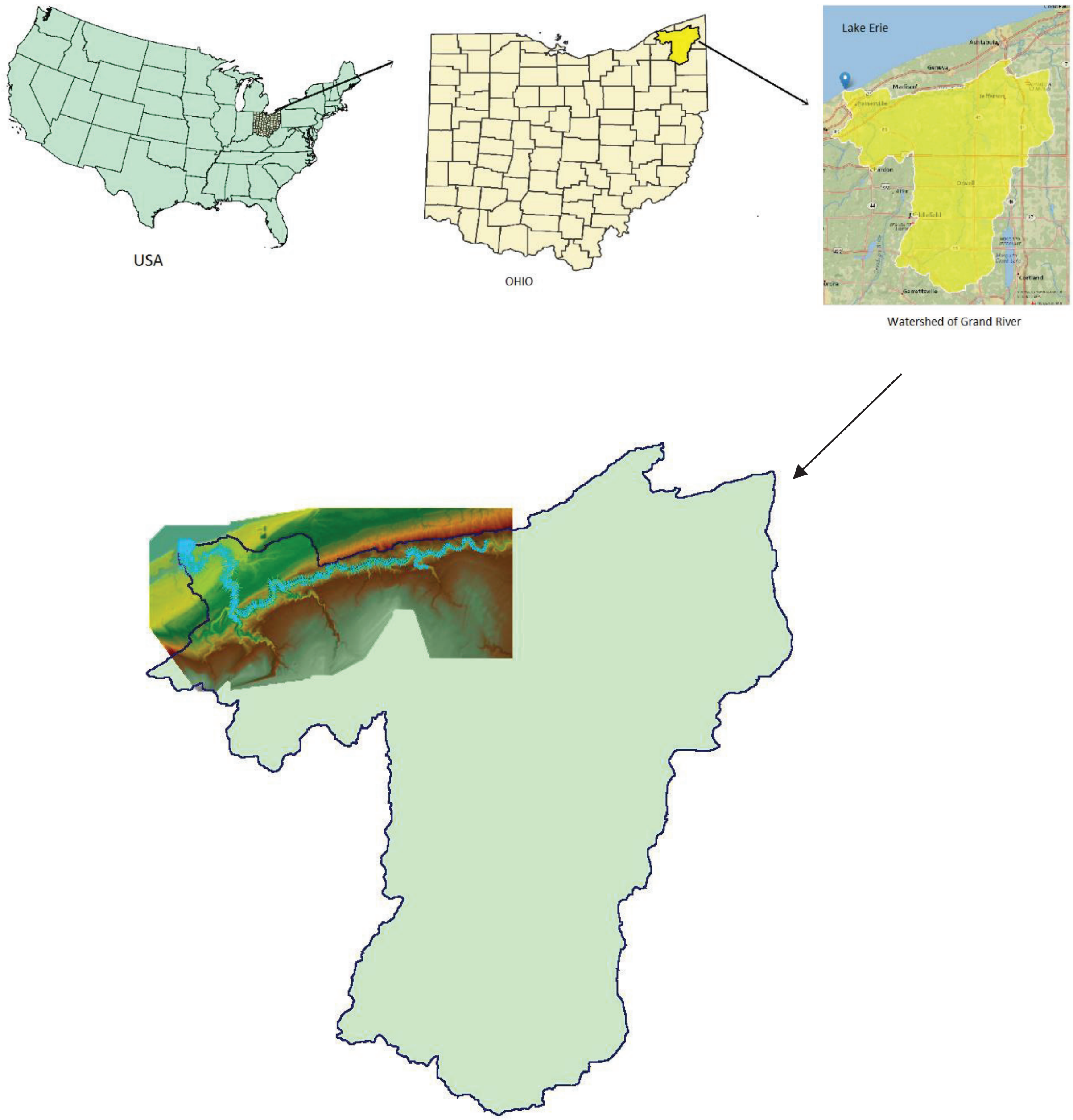
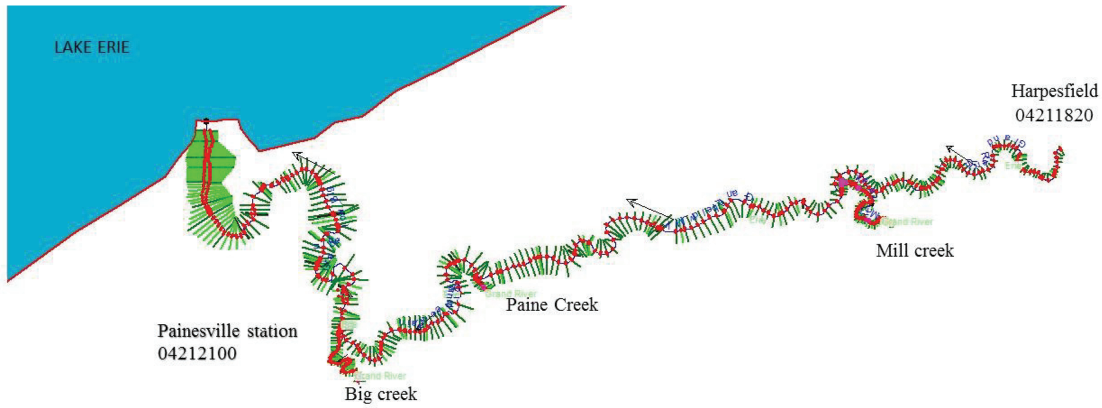


Figure 2-1: Grand River watershed with the modelled river section



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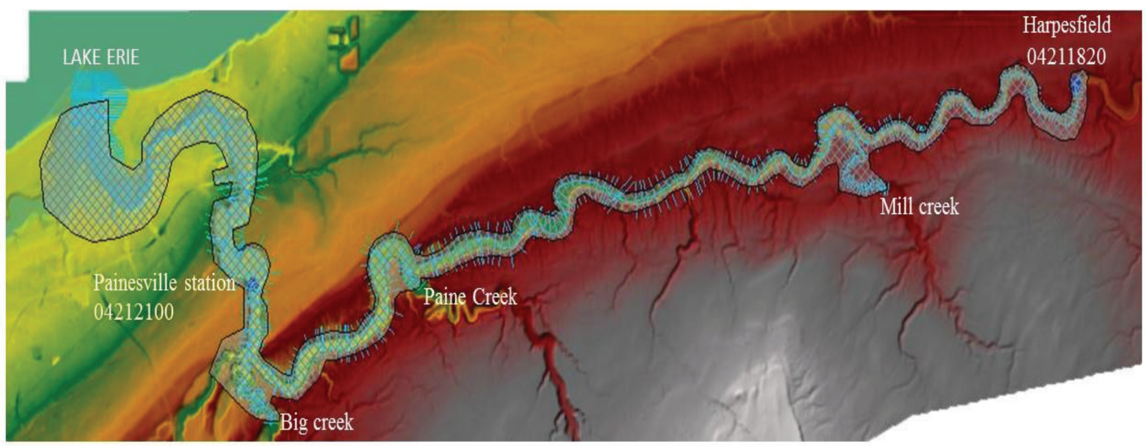

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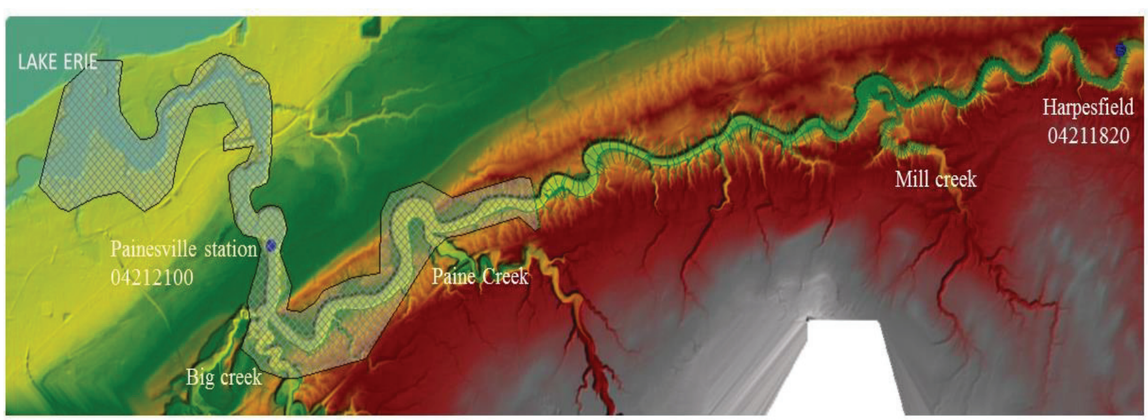

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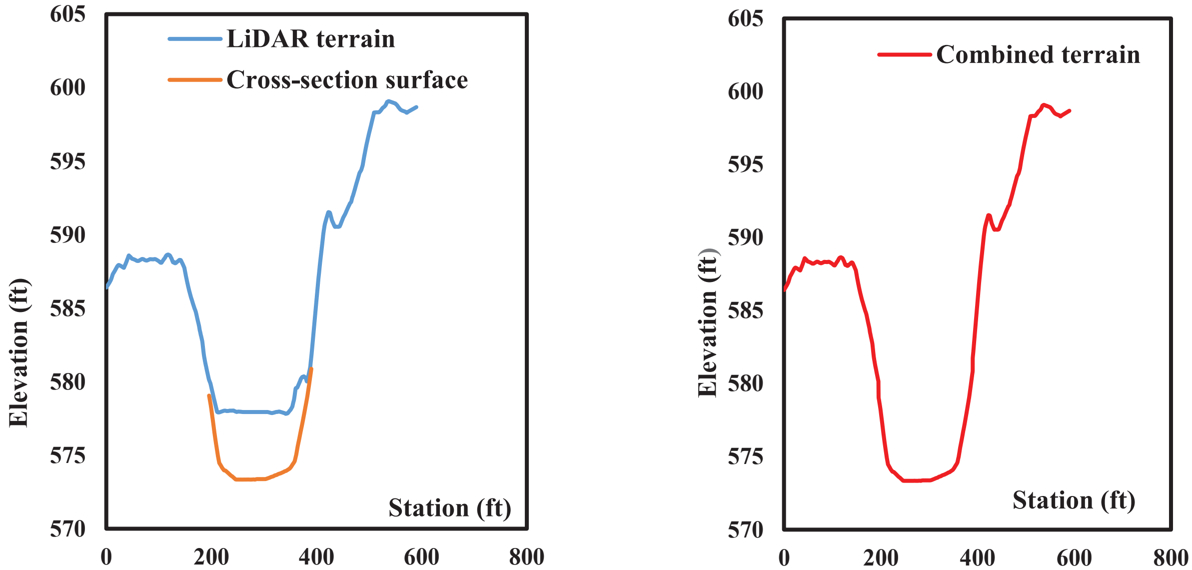
Figure 2-2: Set up of 1D model (a), 2D model (b), and coupled 1D/2D model (c)



(a) (b)

Figure 2-3: Generation of combined terrain for 2D model from surveyed cross section and LiDAR derived DEM (a), combined terrain (b)

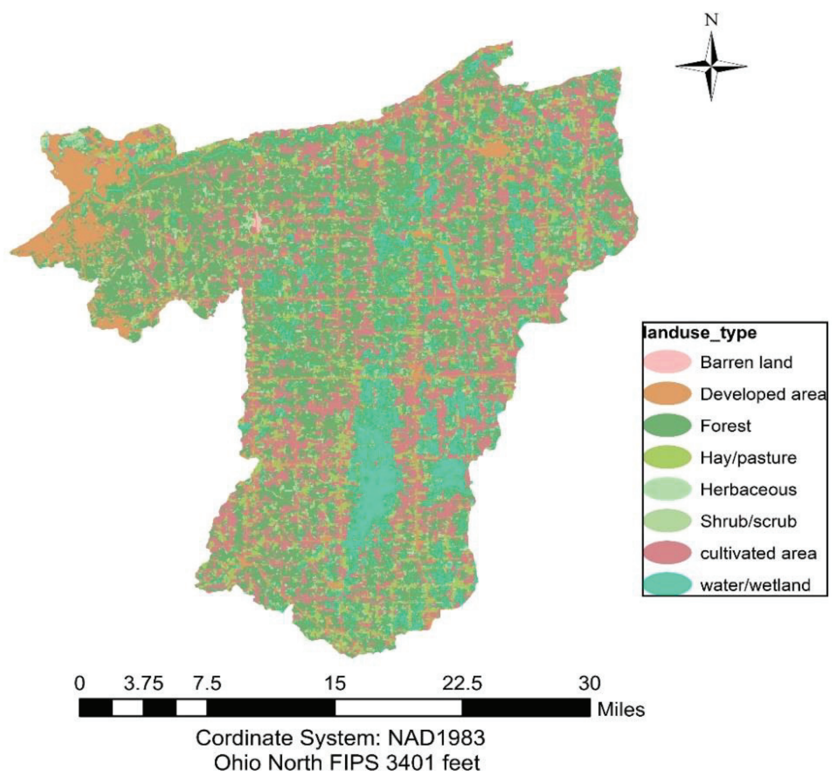
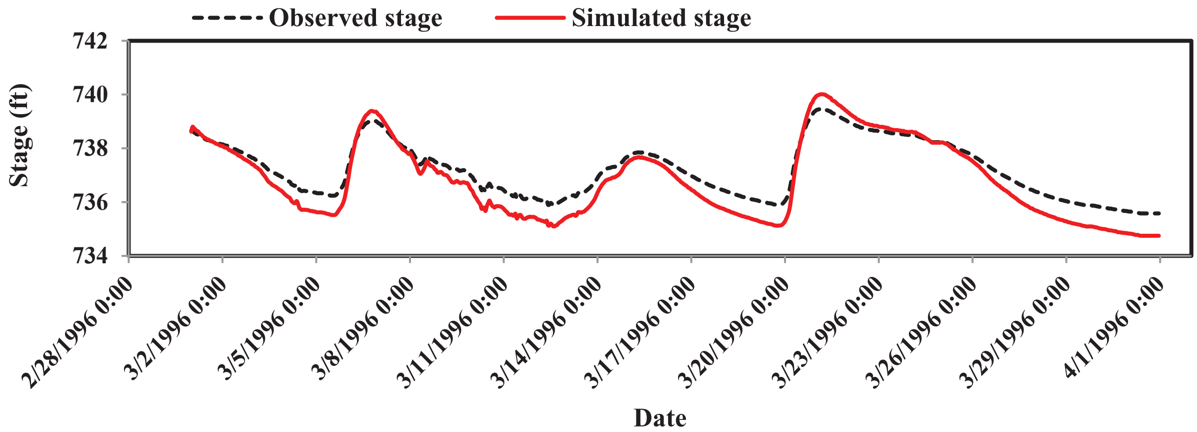
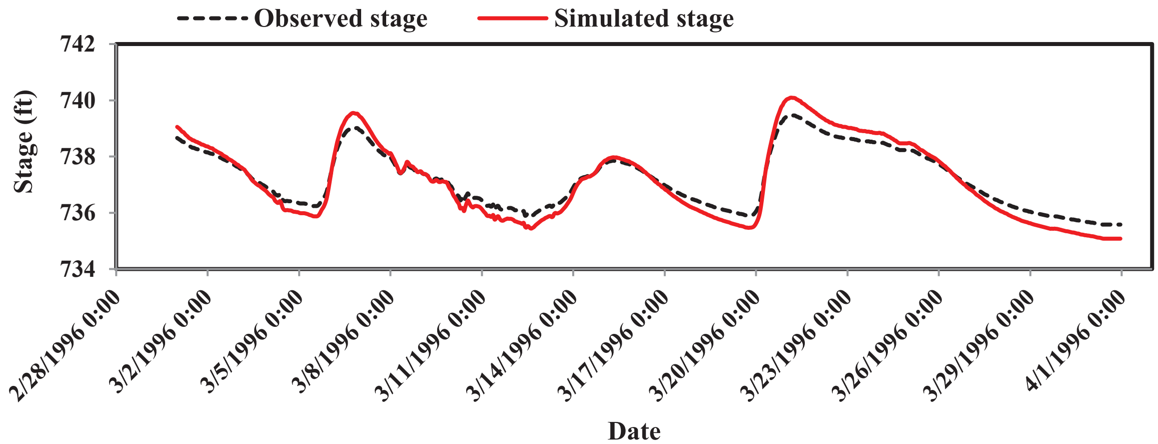


Figure 2-4: Land use of Grand River watershed (NLCD 2011)



(a)



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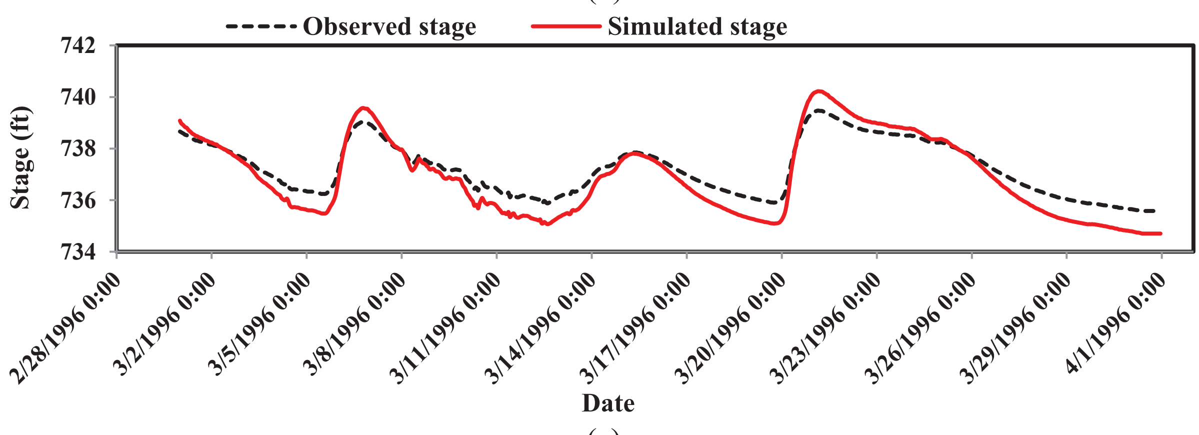
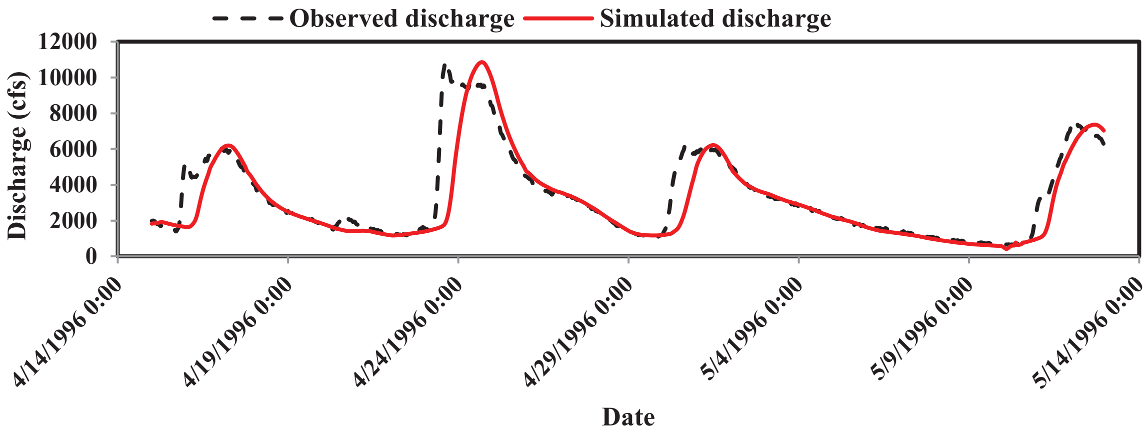
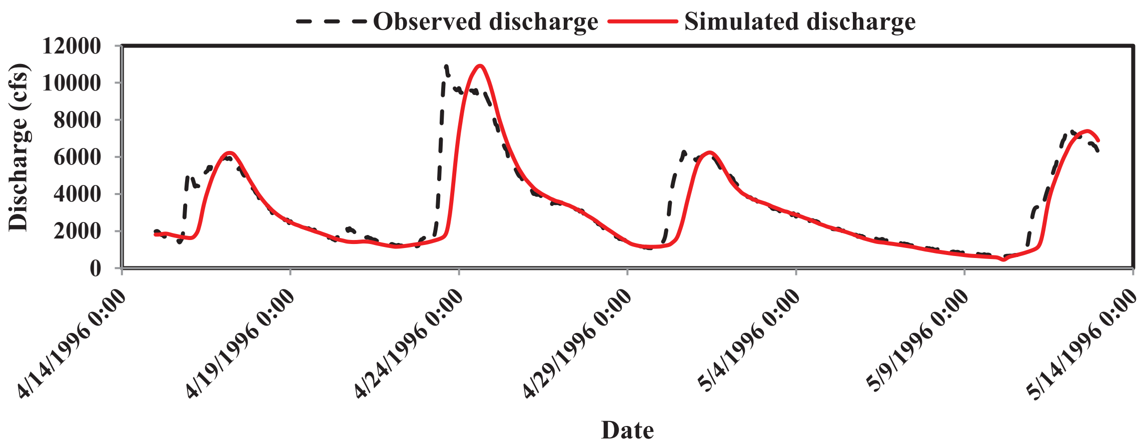


(c)

Figure 2-5: Stage calibration of 1D model (a), 2D model (b) and coupled 1D/2D (c) model, from 03/01/1996 to 03/31/1996 at upstream station (Harpesfield -04211820)



(a)



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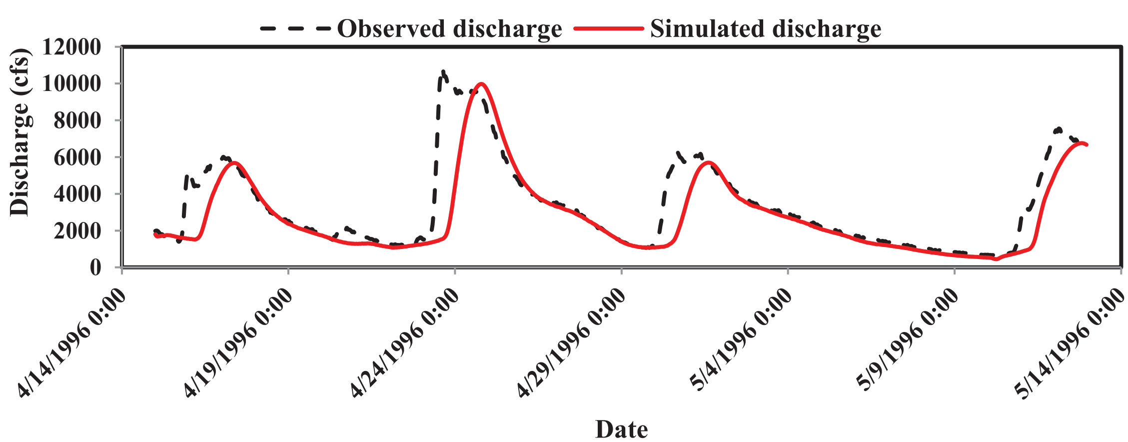

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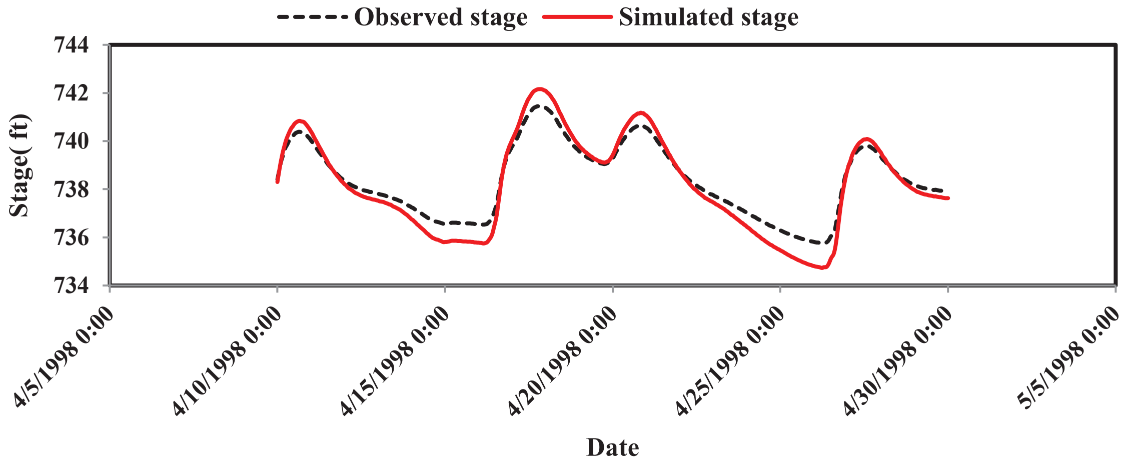
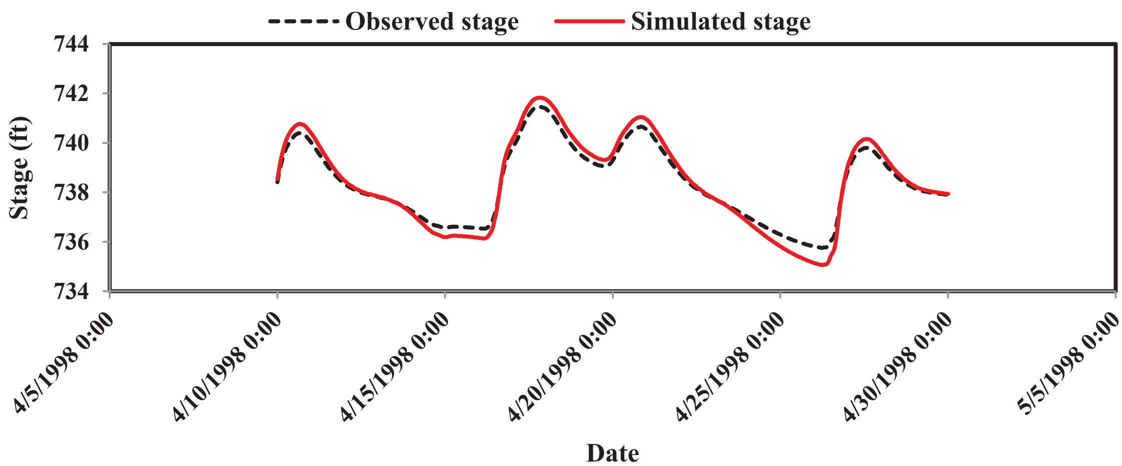
Figure 2-6: Discharge calibration of 1D model (a), 2D model (b) and coupled 1D/2D model (c), from 04/15/1996 to 05/12/1996 at downstream station (Painesville -04212100)



(a)



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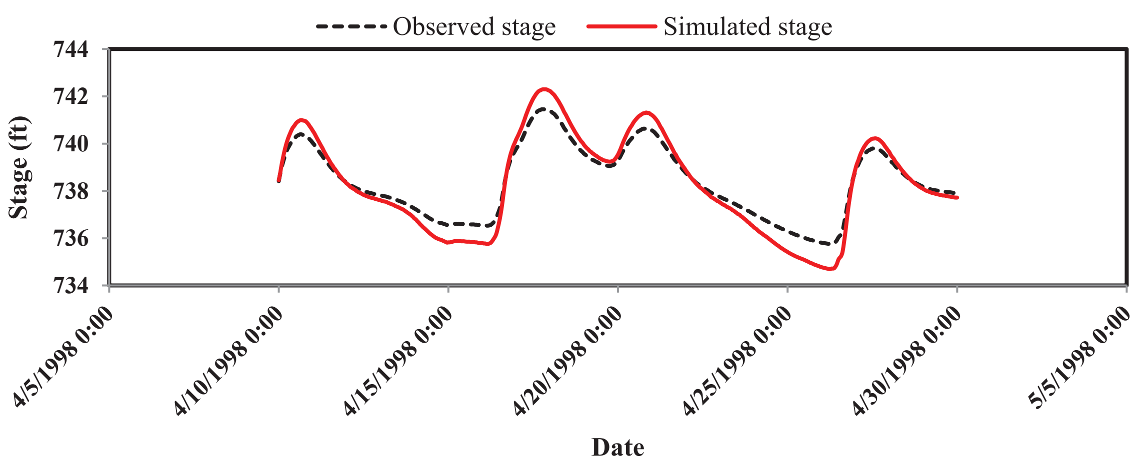


(c)

Figure 2-7: Validation of 1D model (a), 2D model (b), and coupled 1D/2D model (c), from 04/10/1998to 04/30/1998

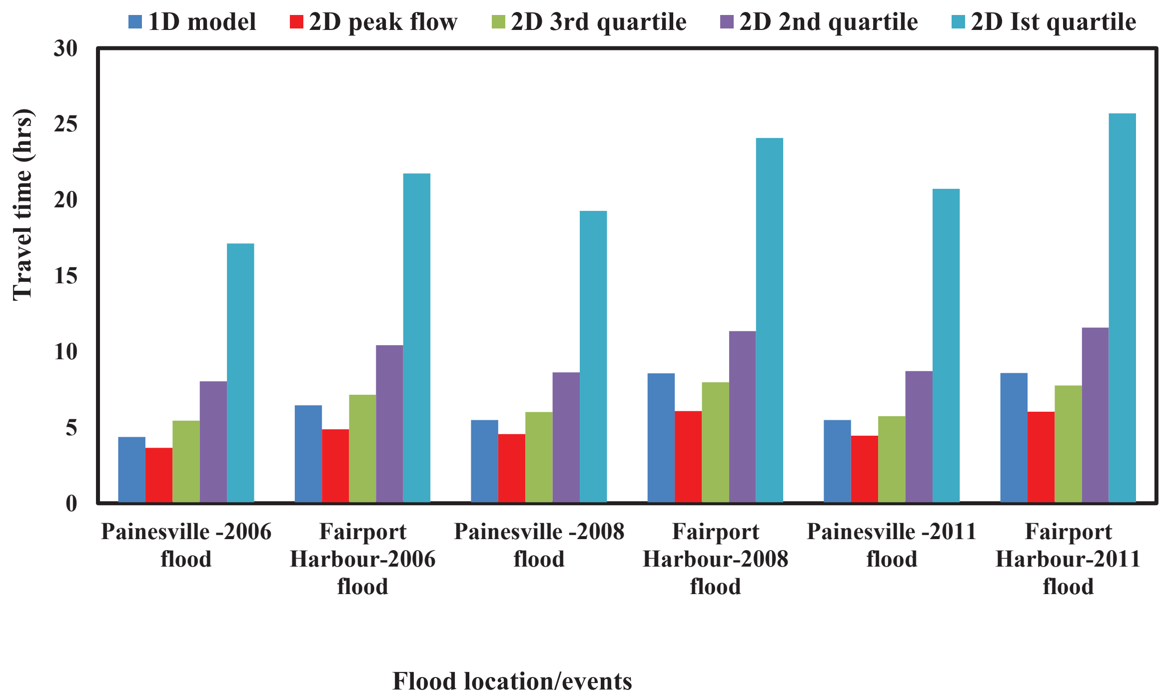


Figure 2-8: Flood travel time comparison of 1D and 2D models for 2006 and 2008 flood events from Harpersfield to Painesville station, and to Fairport Harbor

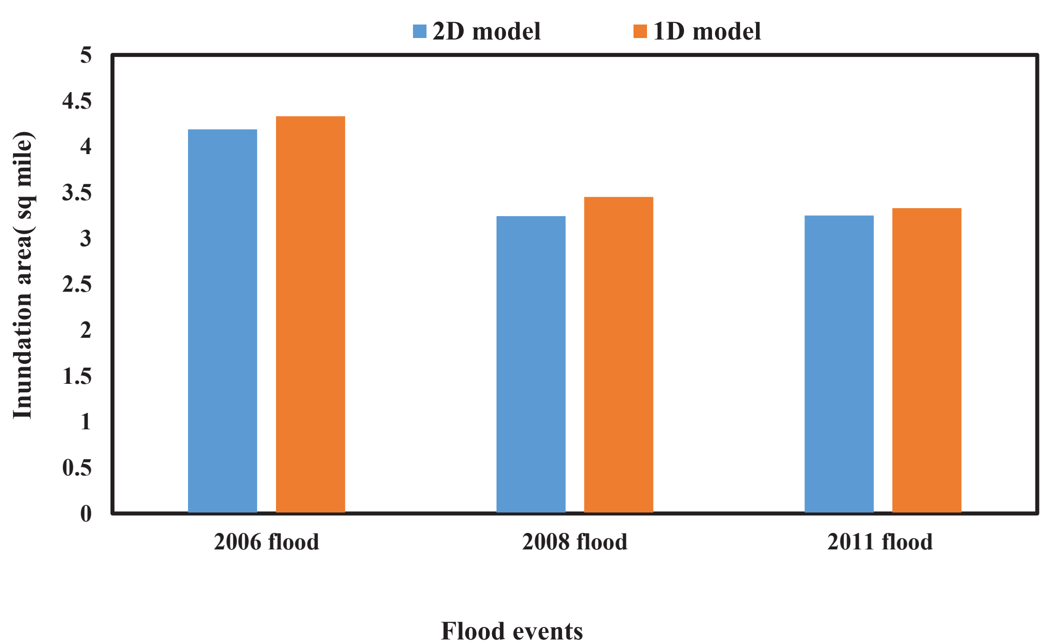
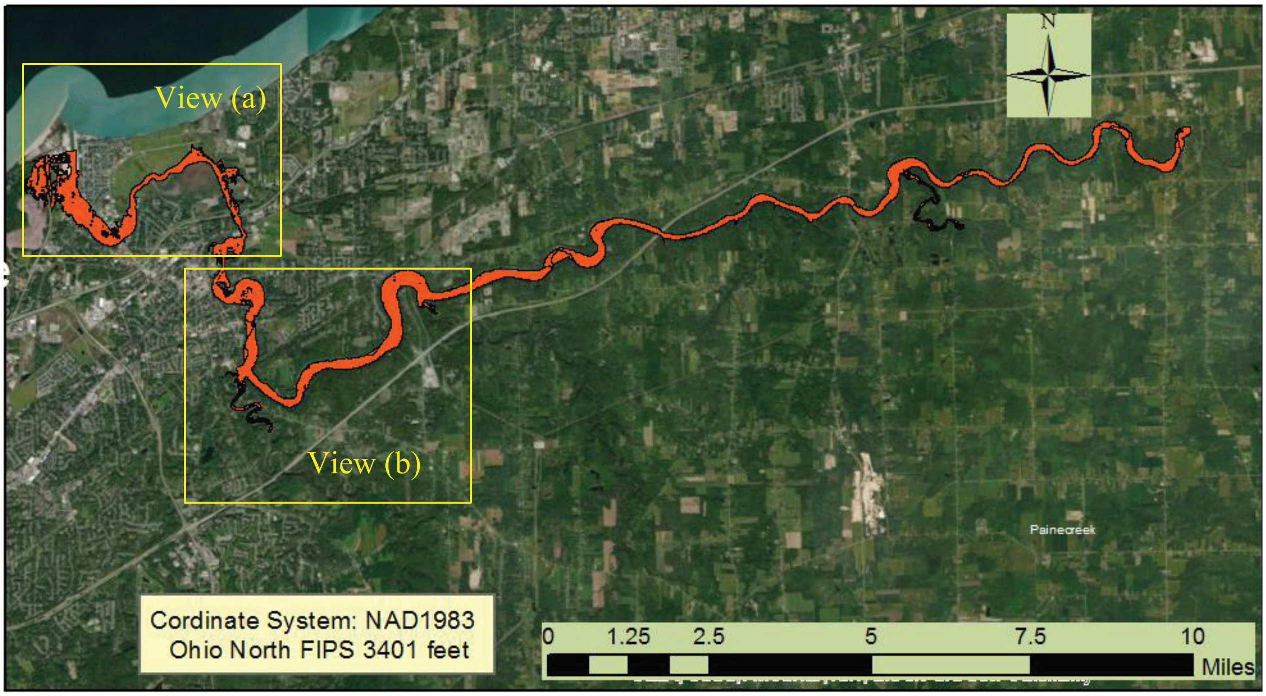
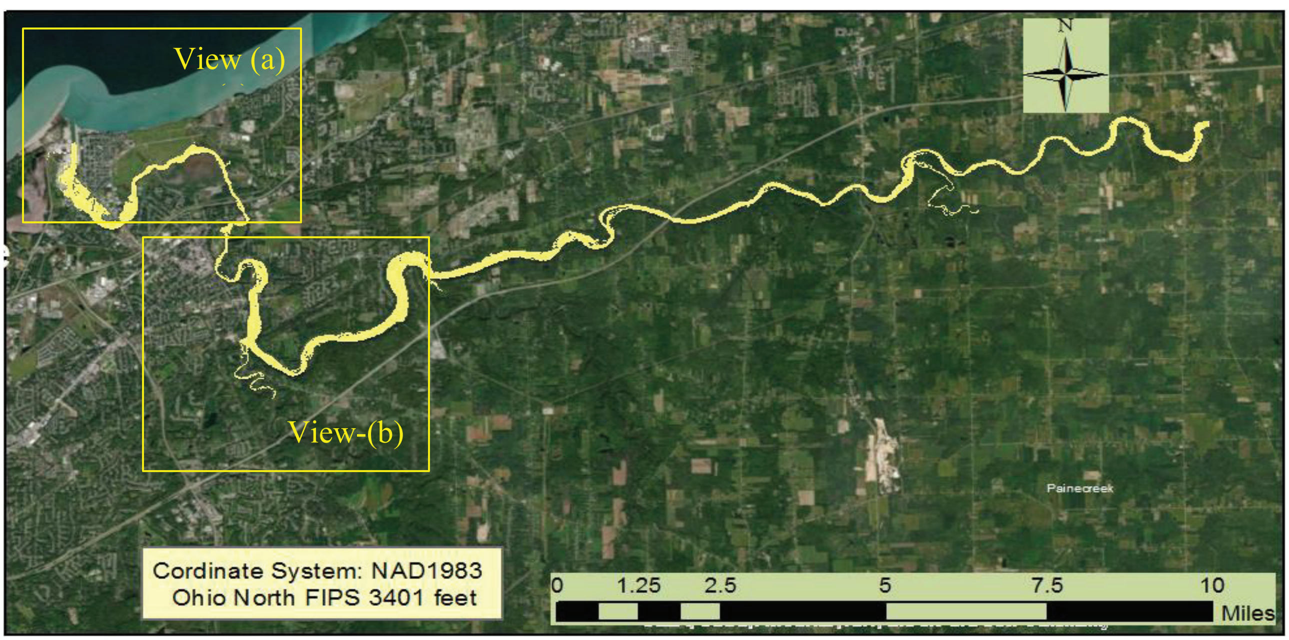


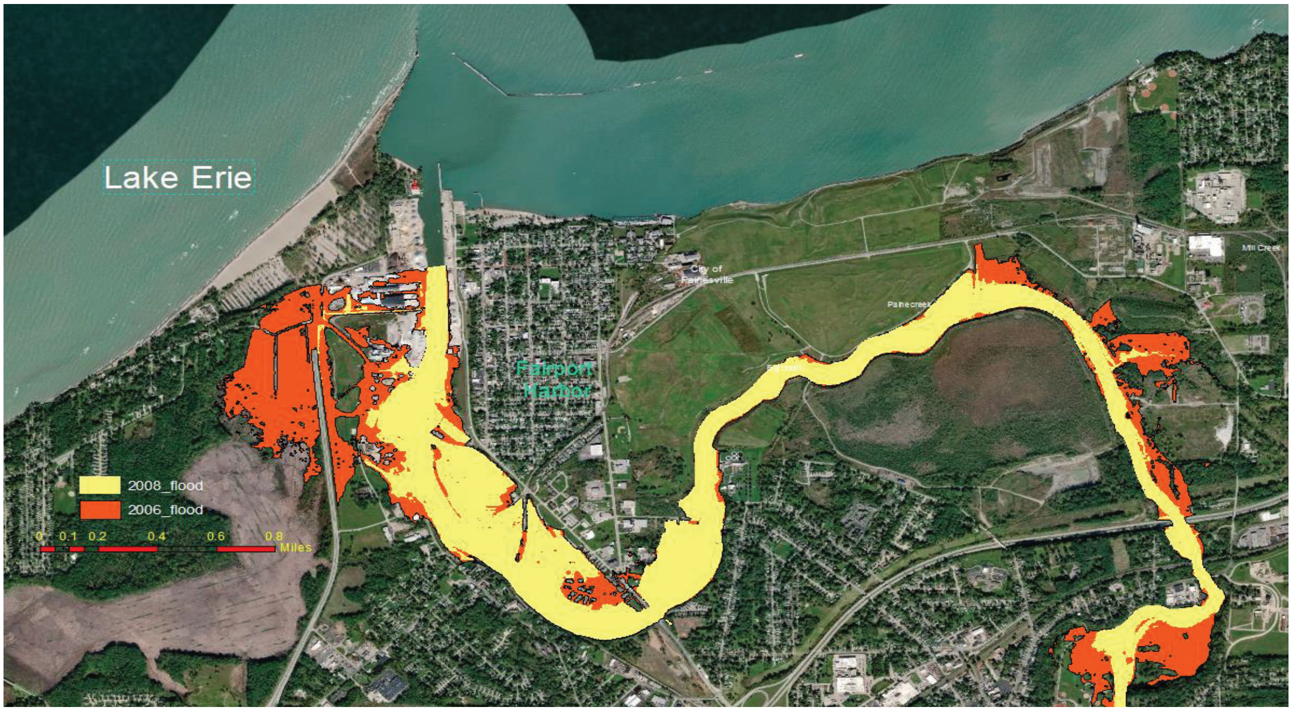
Figure 2-9: Comparison of inundation area of 1D and 2D model for 2006, 2008 and 2011 flood events


View (a)
View (b)
N
Painecreek
Cordinate System: NAD1983
Ohio North FIPS 3401 feet
0 1.25 2.5 5 7.5 10
Miles

(a)


View (a)
View-(b)
N
Painecreek
Cordinate System: NAD1983
Ohio North FIPS 3401 feet
0 1.25 2.5 5 7.5 10
Miles

(b)



(c)

(d)

Figure 2-10: Inundation maps of 2006 flood (a), 2008 flood (b), detailed view near Fairport Harbor (c), and detailed view near city of Painesville (d)

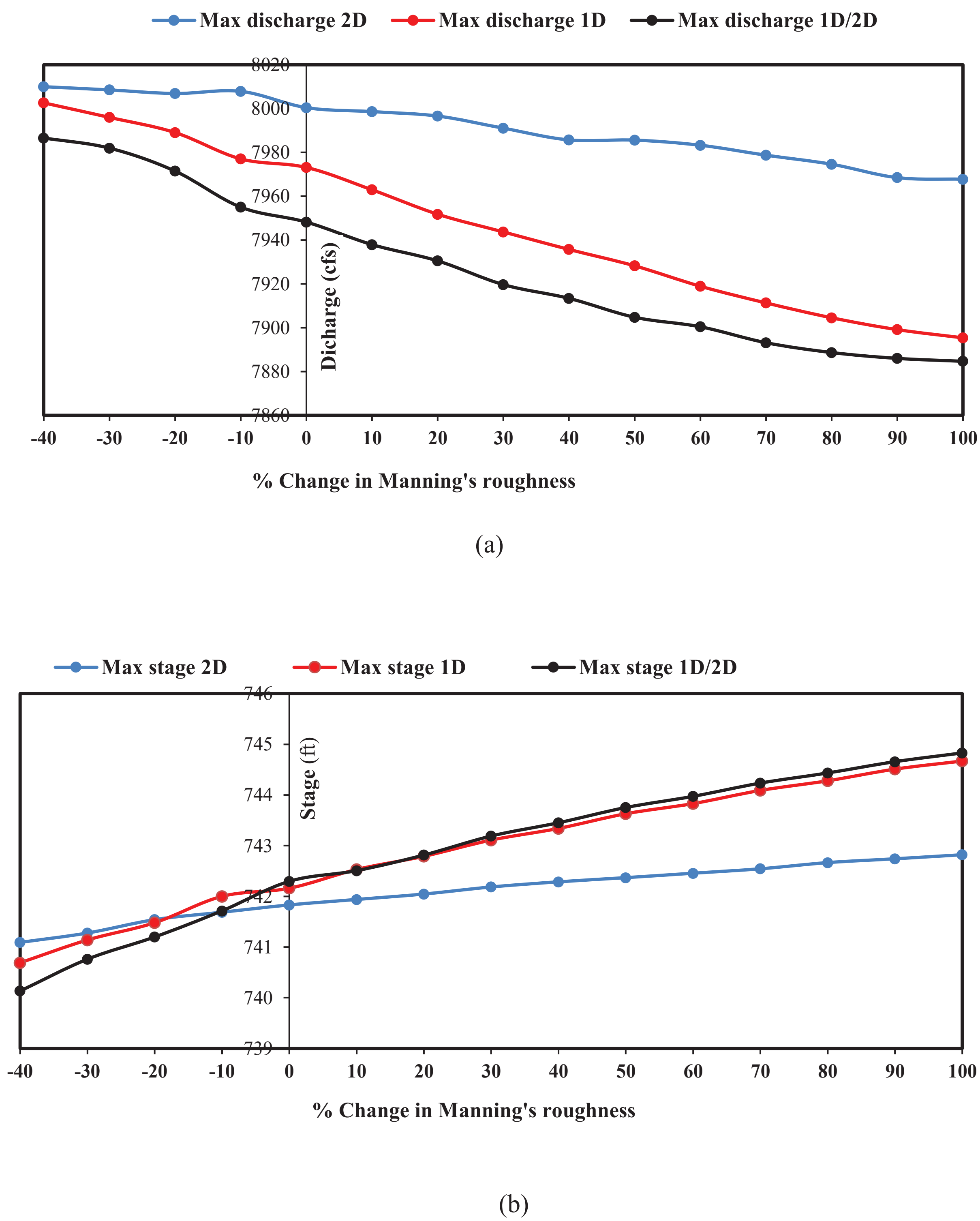
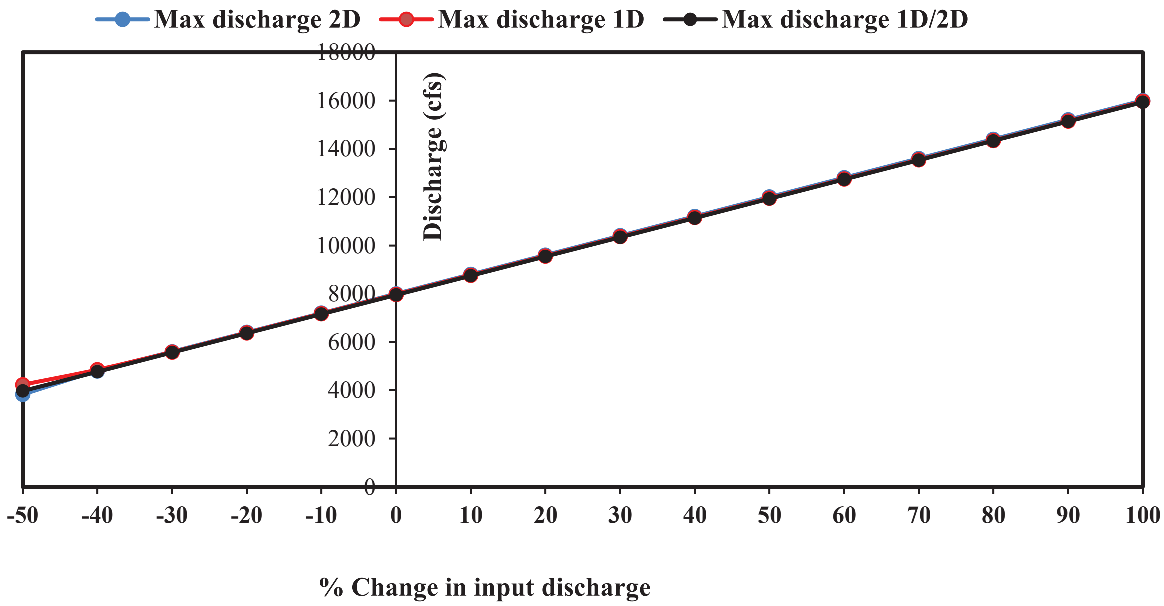
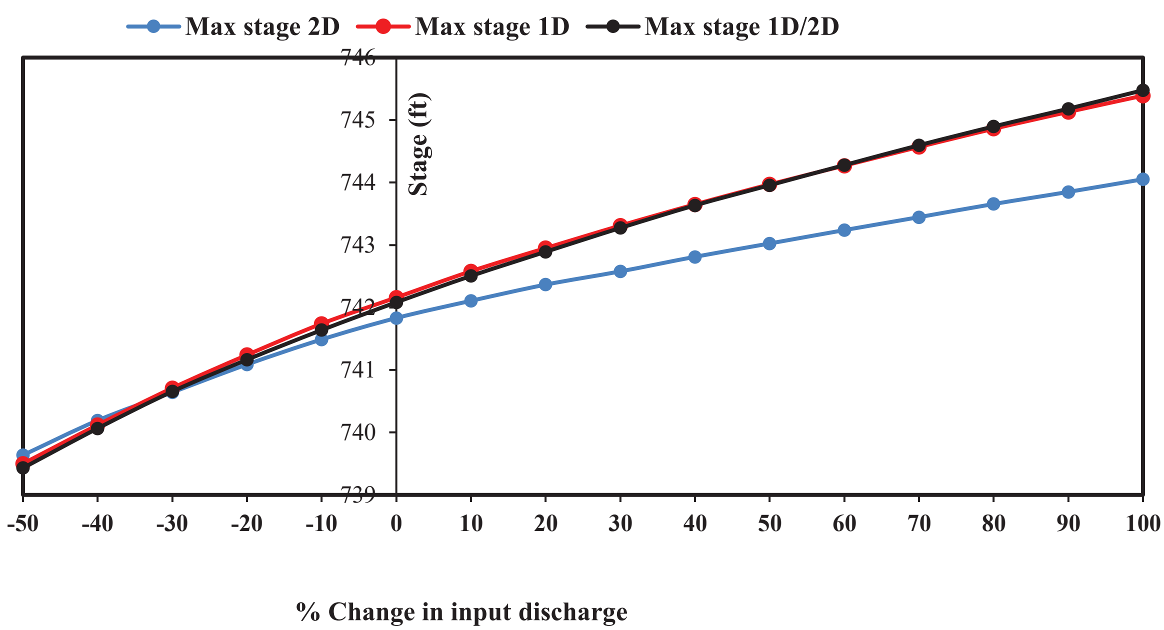


Figure 2-11: Sensitivity of Manning's roughness with discharge measured downstream station (a), and with stage measured on upstream station (b)



(a)



(b)

Figure 2-12: Sensitivity of input discharge with stage measured downstream station (a), and with discharge measured on upstream station (b)

Note: Stage is measured at upstream station (Harpersfield) while discharge is measured in downstream station (Painesville).

Table 2-1: Stage calibration/ validation of the upstream station (04211820) from 1996 to 1998

Stage calibration at 04211820														
SN	Date		Statistical parameter											
			NSE			R^2			PBIAS			RSR		
	From	To	1D	2D	1D/2D	1D	2D	1D/2D	1D	2D	1D/2D	1D	2D	1D/2D
1	3/1/1996 0:00	3/30/1996 0:00	0.74	0.90	0.75	1.00	1.00	1.00	0.05	0.01	0.02	0.51	0.31	0.20
2	4/15/1996 0:00	5/12/1996 23:00	0.84	0.92	0.83	1.00	1.00	1.00	0.00	-0.02	-0.01	0.39	0.28	0.41
3	10/20/1996 0:00	11/28/1996 23:00	0.84	0.92	0.82	1.00	1.00	1.00	0.03	-0.01	0.02	0.40	0.29	0.43
4	2/4/1997 0:00	2/10/1997 23:30	0.83	0.91	0.81	1.00	1.00	1.00	0.02	-0.02	0.01	0.41	0.30	0.44
Stage validation at 04211820														
5	2/26/1997 0:00	3/3/1997 23:30	0.81	0.92	0.83	1.00	0.99	1.00	-0.07	-0.05	-0.04	0.43	0.28	0.42
6	3/5/1997 0:00	3/19/1997 23:30	0.82	0.84	0.81	1.00	1.00	1.00	0.00	-0.03	0.00	0.43	0.40	0.44
7	5/15/1997 0:00	6/6/1997 23:00	0.85	0.94	0.83	0.99	0.98	0.99	0.02	0.01	0.02	0.39	0.25	0.42
8	4/10/1998 0:00	4/30/1998 0:00	0.89	0.96	0.88	1.00	1.00	1.00	0.02	-0.01	0.01	0.33	0.21	0.35

Table 2-2: Discharge calibration/validation of the upstream station (04212100) from 1996 to 1998

Discharge calibration at 04212100														
SN	Date		**Statistical parameter**											
			NSE			R^2			PBIAS				RSR	
	From	To	1D	2D	1D/2D	1D	2D	1D/2D	1D	2D	1D/2D	1D	2D	1D/2D
1	3/1/1996 0:00	3/30/1996 0:00	0.74	0.75	0.74	0.88	0.89	0.86	11.04	11.01	10.28	0.51	0.50	0.57
2	4/15/1996 0:00	5/12/1996 23:00	0.72	0.74	0.81	0.86	0.88	0.91	9.18	9.00	8.57	0.53	0.51	0.44
3	10/20/1996 0:00	11/28/1996 23:00	0.90	0.91	0.90	0.96	0.96	0.96	8.85	9.02	8.87	0.31	0.29	0.31
4	2/4/1997 0:00	2/10/1997 23:30	0.84	0.87	0.84	0.92	0.94	0.92	1.26	1.33	1.30	0.40	0.36	0.40
Discharge validation at 04212100														
5	2/26/1997 0:00	3/3/1997 23:30	0.33	0.40	0.48	0.70	0.73	0.81	5.20	4.97	3.38	0.82	0.78	0.66
6	3/5/1997 0:00	3/19/1997 23:30	0.69	0.74	0.72	0.85	0.88	0.87	7.37	7.45	7.43	0.56	0.51	0.53
7	5/15/1997 0:00	6/6/1997 23:00	0.80	0.81	0.81	0.92	0.92	0.92	-3.34	-3.68	-3.28	0.45	0.44	0.43
8	4/10/1998 0:00	4/30/1998 0:00	0.83	0.86	0.84	0.92	0.93	0.92	3.24	3.21	3.27	0.41	0.38	0.41

Table 2-3: Statistical computations of sensitivity analysis of hydraulic models

Sensitivity of input Manning's roughness						
	Discharge (cfs)			Stage (ft)		
Model	1D	1D/2D	2D	1D	1D/2D	2D
Mean	7969.22			742.49		
Standard deviation	36.28	35.30	15.30	1.26	1.47	0.60
Sensitivity index	0.013	0.013	0.005	0.005	0.006	0.002
Sensitivity of input discharge						
	Discharge (cfs)			Stage (ft)		
Model	1D	1D/2D	2D	1D	1D/2D	2D
Mean	9987.92			742.57		
Standard deviation	3763.67	3795.01	3828.73	1.83	1.88	0.43
Sensitivity index	1.470	1.505	1.520	0.008	0.008	0.006

Chapter 3. Comprehensive Analysis of Flood Damage Assessment Using Various Input Data in HEC-RAS One Dimensional (1D) and Two-Dimensional (2D) Models

Abstract

The assessment of flood damage in the aftermath of a major flooding is one of the crucial steps that the planners, emergency responders and insurance companies are expected to undertake. Assessing the flood damage is very important for the assessing the flood prevention methods, studying flood vulnerability, risk mapping and comparative risk analysis. However, the accuracy of prediction of flood damage model is not only affected by numerous model inputs but also associated with certain degree of uncertainties. Therefore, the overarching goal of this research is to explore how the damage estimation is affected by the selection one-dimensional (1D) and two-dimensional (2D) hydraulic simulation, inventory, and topographic data. The analysis was carried out in the Grand River, near the City of Painesville, northeast Ohio, which encountered frequent flooding over the last several years. The 1D and 2D Hydrologic Engineering Center River Analysis System (HEC-RAS) models were utilized to perform the hydraulic analysis to produce the flood depths. HEC-RAS models were set up for different topographic resolutions including various Digital Elevation Model (DEM) i.e. 30m DEM, 10m DEM and Light Detection and Ranging (LiDAR) derived 3m DEM, which were combined with the filed surveyed river cross-sections data to obtain the flood depths. In order to calibrate and validate the HEC-RAS models, the flow and stage information were obtained from the gaging stations of United States Geological Survey (USGS). Flood loss were estimated by United States Multi-Hazards (HAZUS-MH) developed by Federal Emergency Management Agency (FEMA) for individual building within study region for flood events of different recurrence interval from 10 to 500-year return period. This was accomplished running the analysis by updating the default-building inventory within Lake County from the building data available from Lake county GIS department to represent the realistic building information. The analysis indicated that the 1D model consistently overestimated the loss than the 2D model by an average of 61.48% for the default database and, 86.12% for updated inventory. Moreover, the estimation of the 1D model was consistently higher than that of the 2D model for different sets of topographic resolution and different recurrence interval. The estimation increased with the coarser resolution terrain regardless of modeling techniques. Furthermore, the 2D model revealed lesser percentage increase i.e. to 10.45% in 10m DEM, and to 25.49% in 30m DEM, whereas 1D model exhibited larger increment i.e.to 23.17% in 10m DEM and 76.81% in 30m DEM. Additionally, this analysis suggested that the estimate in an average would decrease by 76.21% after incorporating local building information into the HAZUS-MH database. Additionally, it was found that the higher resolution topographic data is essential for appropriate flood damage assessment.

Keywords: simulation, calibration, validation, inventory, uncertainty, DEM, LiDAR, FEMA

Introduction

Flooding is one commonly recurrent natural disaster resulting in losses of human lives and economic damages (Arrighi et al., 2013; McGrath et al., 2015; Teng et al., 2017). The frequency of flooding events has increased over the last decades (Kreibich et al., 2015). For instance, in the United States alone, federally declared disaster related to flood has exceeded more than 75 percent, and has caused an average loss of 8 billion USD with over 90 deaths per year (USGS, 2019). The damage due to flooding can be reduced through the implementation of flood mitigation measures, assessment of flood vulnerability, comparative risk analysis and risk mapping (Merz et al., 2010). Moreover, damage estimation can be beneficial for creating the flood policies (Wagenaar et al., 2016), making investment decisions (Jongejan and Maaskant, 2013), evaluating risks due to flooding (Kind et al., 2014). However, competent models for flood damage assessment are essential (Dushmanta et al., 2003) in order to assist the stakeholders for the restoration of the floodplains and mitigate the damage caused by the flood.

The development of a fully functional flood damage model is a delicate job as the estimation result are sensitive to interaction of hydrologic and hydraulic analysis, and also to other socioeconomic factors (Jongman et al., 2012; Kriebich et al, 2009; Kelman and Spence, 2004). While the choice appropriate flood model is governed not only by the obtainability of model input data and efforts in computation (Arrighi et al., 2013), also by the objective of the analysis (Jongman et al., 2012). For example, insurance companies are interested to estimate insured damage, whereas the government and academics apply models to estimate the total economic loss (Jongman et al., 2012). There are various flood modeling tools available for damage estimation (Banks et al., 2013; Jongman et al., 2012; Gutenson J. L. et al., 2015). Different countries have different flood assessment tools such as HAZUS-MH in USA (Scawthorn, et al., 2006), FLEMO in Germany (Thieken et al., 2008), SDC in Italy (Amadio et al., 2016), and many more over the world. Jongman et al (2012) carried out the comparative analysis of flood assessment tools used in UK and Germany and attributed the uncertainties in their estimates towards depth-damage curves. Similarly, Banks et al (2013) carried out the review of available tools for flood damage models such as MIKE flood, water RIDE, HEC-FIA and HAZUS-MH, where they identified HAZUS-MH as the best tools for the flood damage assessment. These models were evaluated based on the various factors including affordability, required technical skills, technical supports, capability to conduct hydraulic modeling, and capacity to calculate the damage estimation. Furthermore, Gutenson J. L. et al (2015) also selected HAZUS-MH to be a promising tool among commonly used and freely available flood damage assessment tools including HEC-FDA, HECFIA, and FEMA's HAZUS-MH, in terms of its capability of modeling indirect economic damages and its comprehensive database of predefined structures.

The HAZUS-MH flood model requires the development of flood depth grids to estimate the damage based on the available depth-depth curves developed by FEMA. The HAZUS-MH, on demand, has the ability to generate the stream network and carry out the hydraulic analysis with given topographic data to develop the flood water depth (Gutenson J. L. et al., 2015). However, the result of this default hydraulic analysis are suitable only for the regional analysis and are deemed to be imprecise (Tate et al., 2014). Therefore, researchers in the past (Banks J.C et al., 2014; Dierrauer et al., 2012; Arrighi et al., 2013; Remo et al., 2012; Luke et al., 2015) carried out separate hydraulic analysis to enhance the prediction of the flood impact and imported its result to the HAZUS-MH analysis. Arrighi et al (2013) suggested that the 1D numerical methods are adequate for the estimation of the floodwater depths with unidirectional river flow and well recognized overflow area. However, for the more complex river geometrics and precise flood mapping, 2D model become unavoidable (Apel et al., 2008; Büchele et al., 2006; Ernst et al., 2010). Researchers, Luke et al (2015) and Arrighi et al (2013) have performed quasi-2D hydraulic model-LISFLOOD-FP, adopting the 1D modeling feature in the mainstream river section and 2D modeling feature in wider flood plain for computing flood depths. Since flood propagation in the riverine flood is a two-dimensional phenomenon, the advanced 2D hydraulic model will be more advantageous in flood modeling (Papaioannou et al., 2013). However, based on the author's review, no flood damage models have adopted a fully functional HAZUS-MH model using flood depth grids generated by 2D HEC-RAS.

In addition to the modeling techniques such as 1D versus 2D, the topographic dataset portrays a vital part in the accuracy of damage assessment of a flood model (Koicumaki et al., 2010; Ding et al., 2008; Banks James C. et al., 2014). Banks James C. et al (2014) performed flood analysis to carry out damage estimation using HAZUS-MH with 30m and 10m DEM and suggested that the higher resolution DEM produced better damage estimation. Saksena and Merwade (2015) studied the impact of vertical precision and horizontal scale of DEM on flood inundation and found that higher resolution DEM produced more accurate flood maps and water surface depths. Since HAZUS-MH flood estimation are based on the available stage-damage curves, the overall effect of terrain resolution in flood grid computation gets propagated in loss estimation (de Moel and

Aerts, 2011). Hence, the major goal of this study is to carry damage assessment in HAZUS-MH using both 1D and 2D HEC-RAS model using various topographical resolutions and flood frequency to analyze the effect of mode of simulation and quality of input data over damage assessment. For this, a fully functional HEC-RAS and HAZUS-MH models were developed with different topographic dataset and flood magnitude of different return periods. Furthermore, the difference in damage estimation were analyzed with the updated inventory database. For this, the building inventory data from Lake county office were digitized and imported to HAZUS-MH inventory via FEMA's Comprehensive Data Management System (CDMS).

Theoretical Description

HAZUS-MH

HAZUS-MH is a tool supported by the FEMA originally for USA and currently utilized across the globe, for computing the damage caused by the natural hazards such as wind, flooding, and earthquake at a regional scale (FEMA, 2013). The HAZUS-MH flood model is an ArcGIS based tool, which employs state of art in flood damage assessment based on depth-damage curves developed by FEMA as well by United States Army Corps of Engineers (USACE) (Schneider Philip J. and Schauer Barbara A, 2006). The model is aimed at economic loss (McGrath et al., 2015), quantifying shelter requirement (Vecere et al., 2017), evaluating effect of the flood on society, and helping the mitigation (Blais et al., 2006). This damage estimation model can perform riverine, coastal and riverine/coastal flood hazards at three levels (level 1, level 2 and level 3) of analysis (FEMA, 2013).

The level one analysis requires minimal input from the user and operates based on the default national building inventory database and depth-damage function developed by FEMA and USACE. It utilizes DEM from United Stated Geological Survey (USGS) website, perform hydrologic and hydraulic analysis based on USGS regression equation developed by FEMA to produce depth grid and finally perform the damage assessment with default USGS depth-damage function with default inventory dataset. The level 2 and level 3 analysis enhance the accuracy of the estimation with more detailed information about the terrain and the located building inventory (FEMA, 2013). It allows users to use depth grids developed by hydraulic and hydrologic analysis from the external model such as HEC-RAS, depth grids, Flood Information Tool (FIT). Furthermore, level 2 and level 3 analysis uses more specific/updated information of the building inventory and modified depth-damage curves to develop a more accurate hazard assessment. The quality of details and sophistication of model analysis advances with the increase in the level of analysis in HAZUS-MH model (FEMA, 2013).

Riverine Flood Hazard

Riverine flood hazard analysis is performed in order to develop flood depth-grids to be used in the damage estimation. The hydrologic and hydraulic analysis involved in riverine flood hazard are discussed below:

Hydrologic Analysis

Regression equations has been established at the regional level by USGS for every states which are utilized by HAZUS-MH to carry out the hydrological calculations for the selected stream reaches in the default method of analysis (Jennings et al., 1994). The equation (1) present the form of regression equation formulated by USGS.

$$Q_T = C\, f_1\,(P_1)\;\; f_2\,(P_2) \ldots\ldots\ldots\ldots\; f_n\,(P_n) \qquad (1)$$

Where,

Q_T represent the flow value of specific return period of T; C refer to a constant; f_i (P_i) represent the the function of the i^{th} parameter in regression equations. The value and category of parameter differs with each equation. The detailed theoretical description of the hydrological analysis can be found on HAZUS-MH flood technical manual.

Hydraulic Analysis

The hydraulic analysis is carried out to calculate flood depth grids along the river section (FEMA, 2013).The level one hydraulic analysis uses Manning's equation and bed slope of the reach to perform the hydraulic analysis. The flow value is interpolated in floodplain using power functions of basin area. Flood depth with default method are developed by subtracting the ground elevation water surface at each cell in DEM to form a floodplain. There are other options available in HAZUS-MH to import the pre-processed depth grids such as from Flood Information Tool (FIT), user-developed depth grids and depth grids from HEC-RAS.

HEC-RAS

The hydraulic modeling have been performed with 1D and 2D HEC-RAS for the generation of flood depth grids. Both HEC-RAS models have been described in detail in Chapter 2 under heading "Theoretical Description".

Flood Loss Estimation

Inventory Database

The HAZUS-MH model works on default aggregate database at national level that contains the information including general building stocks (as per square footings, occupancy type, building counts etc.), essential services (police station, schools, hospitals ,fire stations), potential loss facilities (nuclear plants), conveyance systems (roads and bridges), and utility services (electricity, drinking water, gas). The inventory also keep the records of hazardous materials, agriculture data, population data and vehicle information (FEMA, 2013). These inventory databases are aggregated at census block level based on US census data of 2010. Quality of default data varies depending upon the source of data and effort expended on it (Muthukumar, 2005). Nevertheless, the accuracy of the estimation of the HAZUS-MH model can be enhanced by updating the inventory data in the specific flood hazard area using a GIS interface tool (CDMS), a tool developed by FEMA (Cutrell et al., 2018).

CDMS

The CDMS is a complimentary tool developed along with HAZUS-MH that provide user a flexibility to update the database at their study area (FEMA, 2019). The CDMS streamlines and automate raw data processing from the external data sources (parcel-level data, tax accessory data) into HAZUS-MH compliant data and transfer it into and out of statewide dataset. It allows user to update aggregated data (square footage, building count, content, and demographics), capture various transportation and utilities facilities data, and User-Defined Facilities (UDF). It supports processing the site-specific level and aggregate level information at census block and census tract level.

Damage Functions

Flood damage functions used in HAZUS-MH are essentially the set of stage-damage curves that relates the height of floodwater to corresponding amount of damage in terms of total replacement cost. The depth-damage curves used in HAZUS-MH flood loos estimation are developed by different sources such as Federal Insurance Administration's (FIA), USACE, USACE Institute for water resources (USACE IWR) depending on the study area (Scawthorn Charles et al., 2006). For the loss estimation, depth-damage curves are chosen by HAZUS-MH from the library based on the type and its content (FEMA, 2013). The damage curves depend on numerous factors such as occupancy class, type of building, type of foundation, building age, first-floor elevation, and depth of flooding.

Materials and Methodology

Study Area

This analysis was performed in the Grand River (Figure 3-1), in northeast Ohio including Lake and Ashtabula County. The two counties taken in the study area includes 7470 census blocks. HAZUS-MH aggregated at census block level includes 137,318 buildings (91.9% residential) with estimated 42,817 million total replacement cost (excluding content). The study region has total estimated population of 331,158 residents, spread over 134 thousands homes (Census Bureau, 2010). Further description of study area can be found in Chapter 2 under heading "Study Area".

Overall Modelling Approach

In order to perform the flood damage estimation on Grand River, HAZUS-MH flood model was set up at level 1 and level 2 analysis at census block level including

Lake and Ashtabula County. At first, level 1 analysis was carried out with default HAZUS-MH procedure using 30m DEM from USGS to calculate the damage assessment. In the next step, level 2 analysis was conducted with updated building inventory available from Lake County to increase the correctness of estimation. For performing the damage analysis, the flood depth grids were imported from the separate hydraulic model (HEC-RAS analysis). The brief overview of running HAZUS-MH analysis with imported HEC-RAS depth grids is presented in Figure 3-2. The flood depths generated by the default HAZUS-MH methodology are deemed to be imprecise and suitable for regional analysis (Tate et al., 2014). More accurate flood depth grids were prepared using 1D and 2D HEC-RAS for the comparative loss estimation. The HEC-RAS models were successfully calibrated and validated using a series of flood events from 1996 to 1998 obtained from the USGS gage station at Painesville and Harpersfield. For the loss estimation, HEC-RAS depth grids generated from various sources of elevation data including 30m, 10m, 3m LiDAR derived DEM from 1D and 2D models for various flood event including from 10 years to 500 years return period flood were used in analysis.

The default inventory database being aggregated at census block level can introduce more errors (Walls and Kousky, 2014). Therefore, I included Parcel-level data from the Lake County to update the inventory. The parcel level data was obtained from the GIS department of Lake County office. The parcel data was digitized and successfully imported into HAZUS-MH database after making them compatible with HAZUS-MH data inventory using ArcGIS and CDMS techniques. The loss estimation was performed with 1D HEC-RAS depth grids, 2D HEC-RAS depth grids and the depth grids of the default HAZUS-MH methodology.

Data Sources

Hydraulic Data

Though several studies were conducted in the past, it has not been clear yet whether 2D model is better for flood damage assessment compared to 1D model. Therefore, both HEC-RAS models were used for flood modeling in order to compare effects of the modeling techniques in damage assessment. The elevation data required to set the hydraulic models were the LiDAR data obtained from Ohio Geographically Referenced Information Program (ORGIP). Similarly, the 30m and 10m DEM were taken from National Elevation Dataset (NED) data, which were available at USGS. Likewise, the land cover data were extracted from National Land Cover Dataset (NLCD 2011). The land use characteristics used during flood modeling consists of 41.81% of forest, 24.54% cultivated, 10.31% developed, 9.258% hay/pasture, 7.67% water/wetland, 4.19% emergent herbaceous, 2.12% Shrub/scrub and 0.08% barren land area. The land use types were used to select the Manning's friction coefficient for the development of 2D model.

The hydraulic models were calibrated changing Manning's roughness to suitable values using the series of flow data. The flow and water surface elevation information used in the models were taken from USGS gage stations at Harpersfield (04211820) and at Painesville (04212100) from the various event from 1996 to 1998. After the successful model calibration and validation, the hydraulic model were used to generate the flood heights, which were imported in the HAZUS-MH for loss estimation.

Hydraulic Model Calibration and Validation

The HEC-RAS models were calibrated up to optimum values of Manning's coefficient by relating the observed river flow and flood height with their modeled counterparts. The values for starting Manning's coefficient used in the model were based on the visual inspection of the channel at several locations. For example, M. S. Horritt and Bates (2000) showed that the Manning's coefficient for the main river channel ranged from 0.01 to 0.05 and for flood plain it ranged from 0.01 to 0.02. Chow et al (1998) provided the working range of friction coefficient between 0.035 to 0.065 for river section and between 0.08 to 0.15 for overflow area. Similarly, Brunner (2016) and Arcement and Schneider (1989) provided the suggested range of roughness values for 2D model. In order to make the calibration parameter tractable, single friction value for river section and flood plain was adopted for 1D model. Each of the hydraulic models was calibrated and validated using series of flood scenarios that were measured between 1996 to 1998 for different sets of Manning's values. The optimum roughness valued obtained from the calibration were used later on to create the flood grids for performing the damage estimation.

Evaluation Criteria for Hydraulic Models

The criteria for evaluating hydraulic models is explained in detail in chapter 2 under heading "Model Evaluation Criteria".

Building Inventory Data

The default HAZUS-MH analysis uses the inventory data from the HAZUS-MH database aggregated at a census block level. In order to update the building inventory, the building parcel data obtained from the Lake County GIS department were brought into HAZUS-MH database via CDMS and ArcGIS. The parcel data for the Lake County contained information about the market value of the building (replacement cost), an area of building, basement type, and the number of stories. The parcel data was digitized in ArcGIS to represent their existing location. The CDMS essentially requires GIS dataset to the contain the information about building location (longitude& latitude), foundation type, first floor height, building value, content value, occupancy type and number of stories. To bring the parcel data into the format accepted in HAZUS-MH analysis through CDMS, some of the attributes needed to be populated using the guidelines provided by FEMA (Cutrell et al., 2018). The occupancy type was assigned as RES1 (single family dwelling-residential building), foundation type for missing values was populated as 7 (ID), the number of story was 1 for missing values and the first floor for missing values was adjusted using the guidelines of FEMA. The area of building was populated in square feet along with the building replacement cost corresponding to each building from the parcel data. The building content value, which was not present in parcel data, was populated by CDMS itself to be 50% for single-family dwelling (RES1) building type adopted for the missing value.

Effect of River Hydraulic Modelling Techniques

The default hydraulic model in HAZUS-MH uses USGS regional regression equation for hydrological analysis and compute the flood depth surface based on the input terrain. However more accurate user-supplied hydraulic model such as HEC-RAS can create substantial difference (Tate et al., 2014) while creating height of flood water as well as estimating the flooded area. In many cases when flow pattern are uniform and unidirectional, 1D model are taken satisfactory enough for computing of flood water heights and creating the flooding arteea (Büchele et al., 2006). However, for more accurate analysis in complex river geometrics and wider flood plain, 2D model is essential (Büchele et al., 2006). Regardless, the selection of model depends upon the available resources, complexity and computational cost. In this analysis, 1D and 2D HEC-RAS models are compared to see the quantitative differences in riverine flood modeling technique used in loss estimation.

Effect of Inventory Data

The FEMA maintains the national building inventory database aggregated at a census block level. The default method of analysis uses an aggregated approach, which considers building structures to be evenly distributed across a census block (Cutrell et al., 2018). The aggregated approach can be suitable for understanding the flood risk as this approach may overestimate loss in some areas, while underestimate in some others (walls and kousky, 2014; Shultz Steven, 2017). For the smaller geographic area, aggregate approach can induce large error (Walls and Kousky, 2014). The HAZUS-MH model output with default data can have bigger margin of error (FEMA, 2013). Therefore, in order to increase the accuracy of estimation, prior researchers have updated the inventory database in the their study area (Dierrauer et al., 2012 ;Remo et al., 2012 ;Luke, 2015 ;Walls and Kousky, 2014). The inventory database is primarily updated based on the parcel-level data available from local sources including tax assessor data, revenue department, and county office etc. In this study, building data have been updated from data the available from Lake county GIS department and various analysis have been performed to see the effect of the inventory data on estimation.

Effect of Topography

The use of reliable elevation data is essential for accurate flood map preparation and loss estimation. The DEM describes the stream bathymetry and flood plain topography. The elevation model is a key component because it affects the calculations of river flow in a hydrological model, and flood heights and flood plain boundary in hydraulic model (Cook and Merwade, 2008). Since HAZUS-MH estimation are based on the depth grid generated from a hydraulic model, the overall effect of terrain resolution is also propagated from depth-damage functions in resulting estimates. Banks James C. et al (2015) has shown the improvement in HAZUS-MH model prediction with increase in DEM resolutions. In this study, 30m, 10m and 3m LiDAR derived DEMs have been chosen along with field verified river cross-sections, which ensures the channel bathymetry.

Result and Discussion

Simulation of Hydraulic Model

Both 1D and 2D HEC-RAS model demonstrated good performance, which were evaluated using various statistical indicators. The statistical indicators computed for the observed and simulated model outputs were greater than the suggested values (NSE>0.5, PBAIS ± 25% and RSR ≤0.7) from Moraisi et al (2015). The statistical indicators to evaluate the model performance for both the hydraulic models for stage calibration/validation at Harpersfield station is reported in Table 3-1. Likewise, the model performance for flow calibration/validation at downstream Painesville station is reported in Table 3-2. The coefficient of determination for both the models were 1.0 in most cases. Similarly, the agreement between the measured and modeled water surface elevation at upstream station was observed through the graphical plot for 1D and 2D model as shown in Figure 3-3. The graphical plot of observed and simulated flow measured at Painesville station is shown in Figure 3-4. Even though the graphical and statistical model evaluation indicators were found to be satisfactory for both models, 2D model showed consistently better result than that of 1D model, which was revealed in terms of statistical indicator and visual inspection. Similarly, the model validation was inspected through the graphical plot (Figure 3-5).

Effect of Riverine Hydraulic Modeling Techniques

The effect of modeling technique on damage assessment was evaluated by running HAZUS-MH model importing separate depth grid from 1D and 2D HEC-RAS models. Since there has not been any quantification of the differences in estimated cost using varying degree of topographic data in HAZUS-MH, its output in terms of total replacement cost of building was analyzed for different topographic resolutions including 30m, 10m and 3m LiDAR DEM. The estimated total damage (Figure 3-6) predicted by 2D model was 71.51 million USD for 3m LiDAR DEM with surveyed data, which increased in 1D model to 98.3 million USD with default inventory. The similar increment was observed in 10m and 30m resolutions DEM as reported in Figure 6. Additionally, this damage estimation was substantially reduced after incorporating the local level building inventory data in the model. The estimated total damage reduced to 15.59 million USD by 2D model and 31.8 million USD by 1D model with 3m LiDAR DEM. For various terrain resolutions, the total estimated loss by 1D model was 61.48% more than 2D model for default set of inventory database and 86.12% more in case of updated inventory data . Further, in the analysis refined using only 3m LiDAR DEM with surveyed cross-section and updated inventory data for 100-year and 500-year flood, 1D model continued to show a higher estimation than 2D model (Figure 3-7), both in default as well as updated database. The larger estimation from 1D compared to 2D model could be due to the comparatively poor calibration and less realistic prediction of flood. The difference in 1D and 2D HEC-RAS modeling technique was further supported by Figure 3-8, which showed larger estimate for higher return period event which is in agreement with previous finding of Walls and Kousky (2014) in terms of damage versus return period curves.

Effect of Inventory Data

Since the default sets of inventory data may not represent the actual site conditions, parcel level data was updated in HAZUS-MH database. More importantly, I wanted to see the effect of the quality of the inventory data in flood damage estimation. Since performance of the 2D model was incredibly better than 1D model, the analysis was carried out with 2D HEC-RAS with various resolutions of DEM as input in the HAZUS-MH model one at a time. The DEM resolutions considered for analysis were 30m, 10m, LiDAR, 30m with survey (30m DEM combined with river survey data), 10m with survey, and 3m LiDAR with survey (Figure 3-9). On average, the damage cost estimated with default database was 76.21% higher than that of the cost estimated while incorporating inventory data. This result is consistent with the finding of the earlier research (Ding et al., 2008, Carlson, 2010). Ding et al (2008) found that the default aggregate estimated 65% higher than that of the updated building inventory, whereas Carlson (2010) found that the default analysis overestimated the damage by 51% than that of the actual assessor data. The updated inventory data consistently demonstrated decreased estimation regardless of the resolution of the DEM chosen. The result is promising in the sense that the default inventory considers the uniform distribution of building throughout the census blocks in the analysis (Cutrell et al., 2018) resulting in the overestimation of the number of actual building present. This fact was further supported by this analysis presented in terms of number of damaged building with and without updated database (Figure 3-10). The number of damaged building has decreased from 307 to 144, when estimate was performed with updated data in case of 3m LiDAR DEM. The reduction of the building count was consistent in 10m and 30m resolution, indicating that the coarse resolution would predict more damage count. Furthermore, using updated inventory, the variation of estimated total building damage and number of damaged buildings were calculated to see the damages in relation to flood depths (Figure 3-11). Similarly, the damage estimation relationship with water flow was studied in (Figure 3-12). Presumably, increase in flood depth and flow would damage more buildings and increase the likelihood of the higher damage cost, which was clearly revealed from both these analysis.

Effect of Topography

The influence of the spatial data resolution on the damage assessment was studied by changing the terrain resolution in loss analysis particularly in 2D model. The difference in estimation increased to 10.45% while using 10m DEM, which increased to 25.49 % in 30m DEM. The analyses were also performed in 1D model and the estimated cost further increased. For example, the estimated cost increased to 23.17% while using 10m DEM and 76.81% while using 30m DEM indicating that the estimated cost can be expected to increase with the coarse resolution of DEM. This finding was not surprising because the coarse resolution data cannot be expected to represent the exact river bathymetry and surface features resulting in over prediction in inundation and flood depths and overestimation of the damage cost. In fact, it was expected that the course resolution DEM would overestimate the damage cost as it had a tendency to over predict the inundation of flood plain area (Cook and Merwade, 2009). This result was consistent with the previous finding of Banks J.C. et al (2014), where better spatial resolution data resulted in greater predictability of the flood event. Additionally, the relationship between the flows versus damage estimation was also established the (Figure 3-13). Moreover, the relationship between damage and inundation area as the total increase in percentage damage and inundation area seemed to be positively correlated (Figure 3-14). This finding is also congruent with Gutenson J. L. et al (2014), where the researcher attribute the terrain resolution to play a key role in damage assessment. Additionally, hazard mapping for 2006 flood event presented in Figure 3-15 can be very useful in quantifying spatial distribution of the damage associated during the flooding.

Uncertainties in HAZUS-MH Loss Estimation

Cost assessment model like HAZUS-MH are always subjected to certain degree of uncertainties due to lack of refined data sources, and information about the process causing the damage (Meyer et al., 2013). There are several parameters in flood loss estimation leading to uncertainties in model prediction (Merz et al., 2004) which increases further with the complexity of model (Schröter et al., 2014). Some studies shows these uncertainties stem from hydrological component (de Moel and Aerts, 2010), modeling techniques (Horritt and Bates, 2002) and depth-damage curves (Merz et al., 2011). The HAZUS-MH model estimate involves uncertainties mainly resulting from quality of DEM, calculation of flood depths, accuracy of building database and estimation of a damage model (Tate et al., 2014). In this study, the estimated value of 2006 flood event was 15.6 million USD using 2D model. This analysis included only residential building while commercial, industrial and others were not included. Further, the essential facilities and transportation facilities (roads and bridge) also could not be included.

Conclusion

Quantification of accurate flood damage is essential for flood planning, preparedness of flood hazard, insurance actuaries, emergency response and assessment of flood mitigation measures. While the past research have been limited to HAZUS-MH estimation relying on flood depth calculation from 1D model, this research explores the use of more advanced 2D flood model for flood depth production and to quantify the effect of input topographic dataset and quality of inventory data on the resulting damage estimate. The damage analysis was performed in HAZUS-MH with separate depth grids from 1D and 2D HEC-RAS models for various terrain resolutions including 30m, 10m, and 3m LiDAR derived DEM combined with surveyed river cross-sections for the flood event of different recurring interval including 5 year, 25 year, 50 year, 100 year, 200 year and 500 year. The analysis suggested that 1D and 2D HEC-RAS modeling have a crucial effect in damage assessment. The difference in estimation between 1D and 2D model was larger while using 30m DEM or 10m DEM (coarse resolution) as compared to 3m LiDAR data (fine resolution). The 1D model consistently over predicted the damage than that of the 2D model regardless of the DEM resolutions. The analysis indicated that the selection of the hydraulic model is an inevitable when performing a flood damage assessment. This analysis safely concludes that the use of 2D model to predict the flood depth is more realistic and precise than the use of 1D model because of smaller variation during damage estimation.

Furthermore, the analysis with varying topographic resolutions revealed that the fine resolution LiDAR data showed less inundation area as well as less estimated damage than that of coarser resolution terrain. The damage estimation and the inundation area increased in 10m DEM, which further increased while using 30m DEM indicating that the flood damage assessment is, by and large, depends on the quality of the terrain. The analysis also indicated that high-resolution terrain would be an appropriate selection for the realistic prediction of flood damage.

Moreover, the building database within its study region were updated using the parcel data from the Lake County office GIS department to include the actual representation of building in the model. The estimation of 1D model was consistently higher than that of 2D model in both the default inventory and the updated inventory database. On average, HAZUS-MH analysis with default database had 76.21 percent higher estimation than the updated the database. Additionally, the number of damaged building was also reduced with the use of updated database. The over estimation with default inventory continued to be prevalent in all the topographic resolutions. The analysis showed that incorporating building data within the study area enhanced the damage assessment regardless of modeling technique and terrain resolution suggesting that updating the inventory database leads to the more accurate flood damage assessment compared to default analysis.

While this research tried to explore some of the principal elements for accurate and realistic quantification of flood damage, there might be several other factors contributing uncertainty in model prediction. It could be noted that the HAZUS-MH model estimation could be affected due to the propagation of error in hydrological and hydraulic pre-processing to generate depth grids. Therefore, it is recommended to utilize the probabilistic method of flood frequency study to account the uncertainties and conduct in-depth global sensitivity analysis to quantify the uncertainty before using the result.

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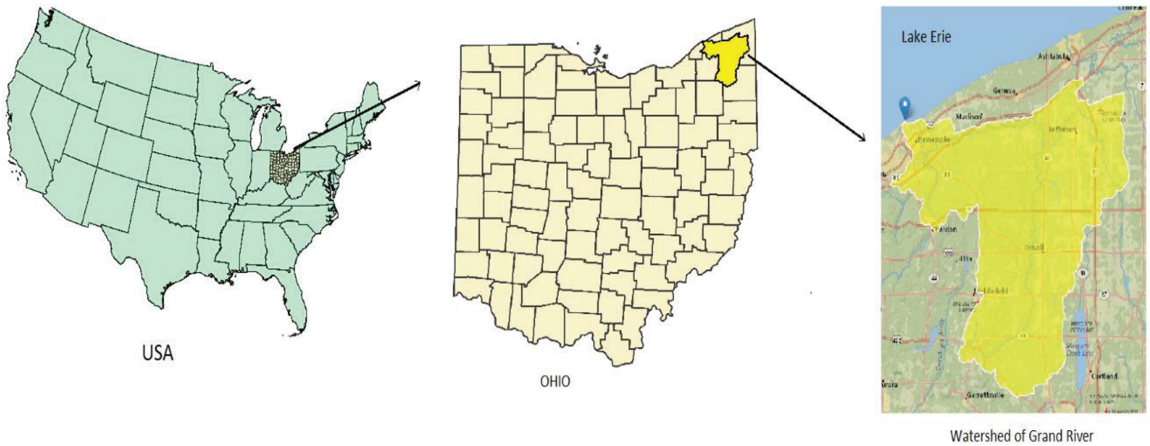
Figures and Tables:



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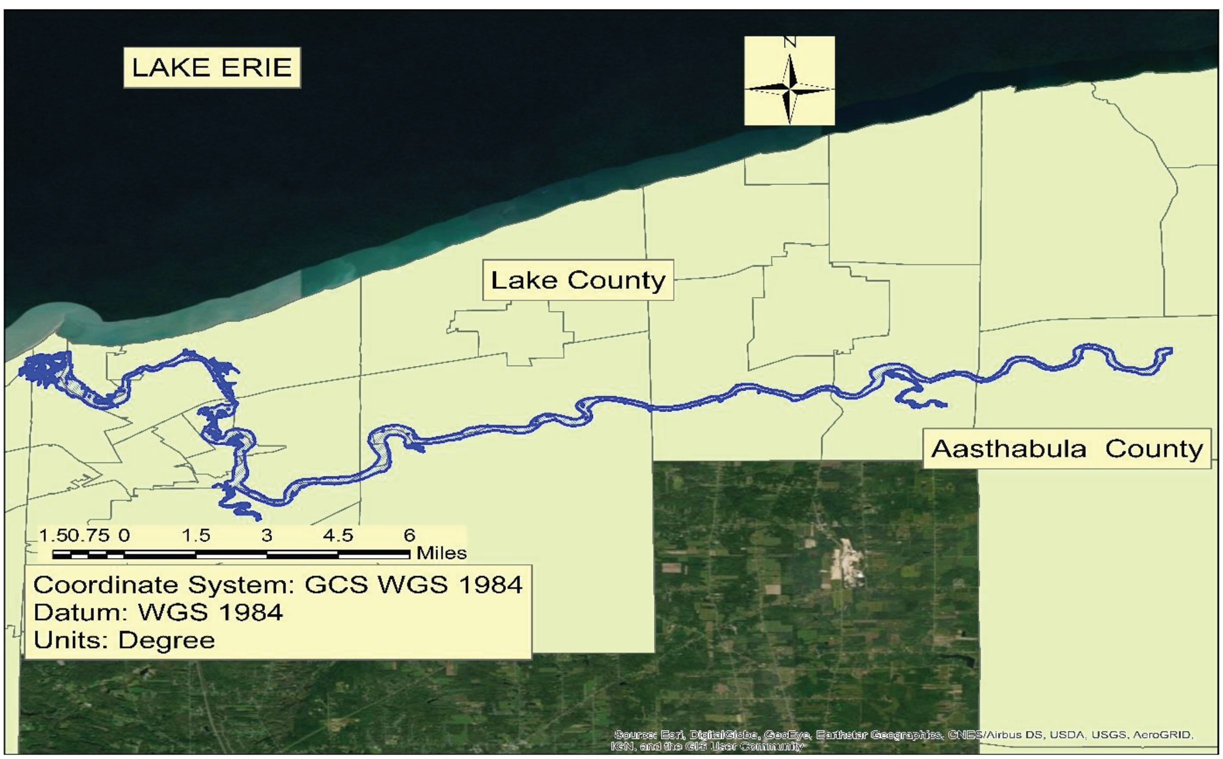


(b)

Figure 3-1: Study area with Grand River watershed boundary (a), HAZUS-MH model boundary region (b)

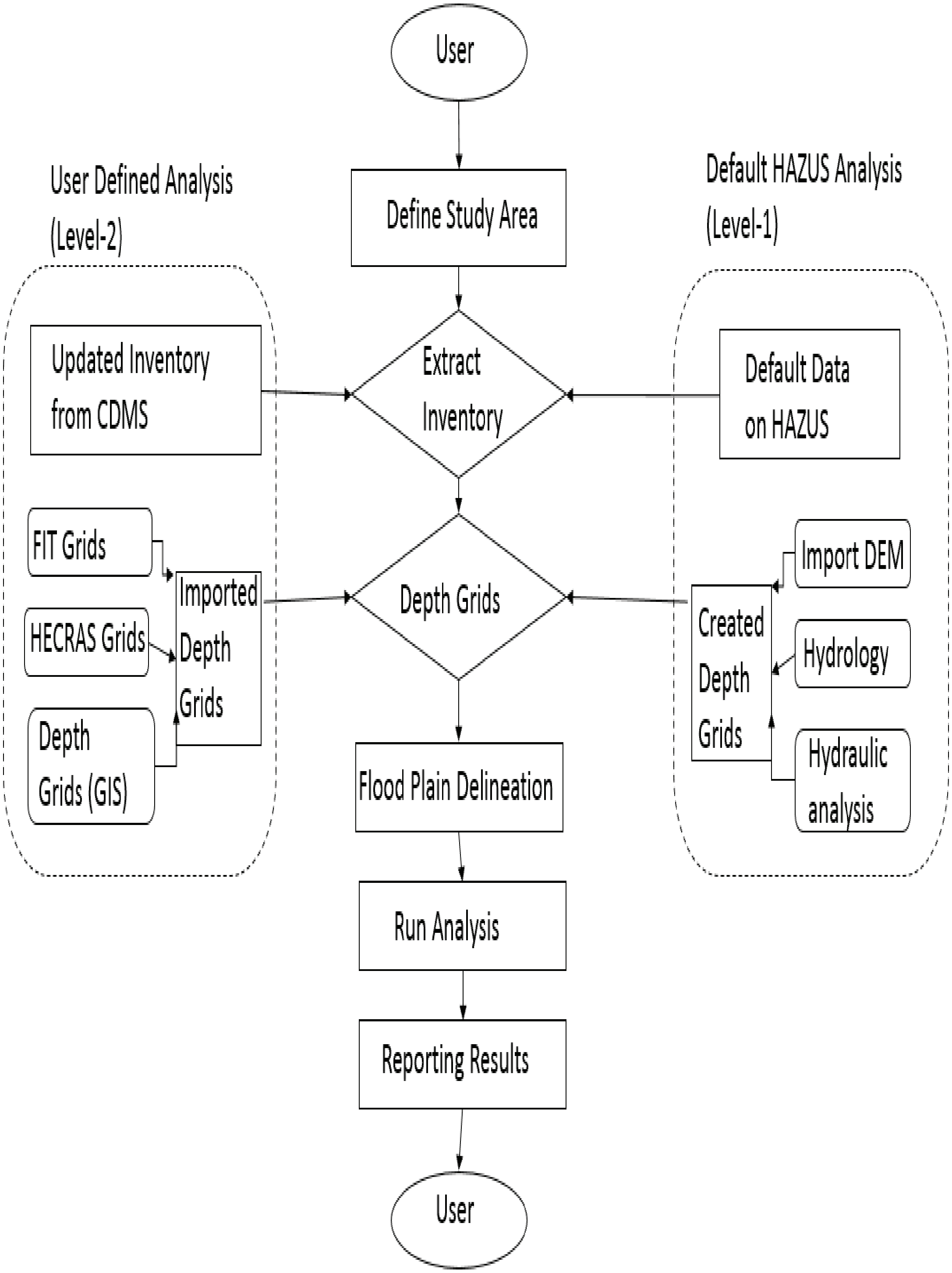
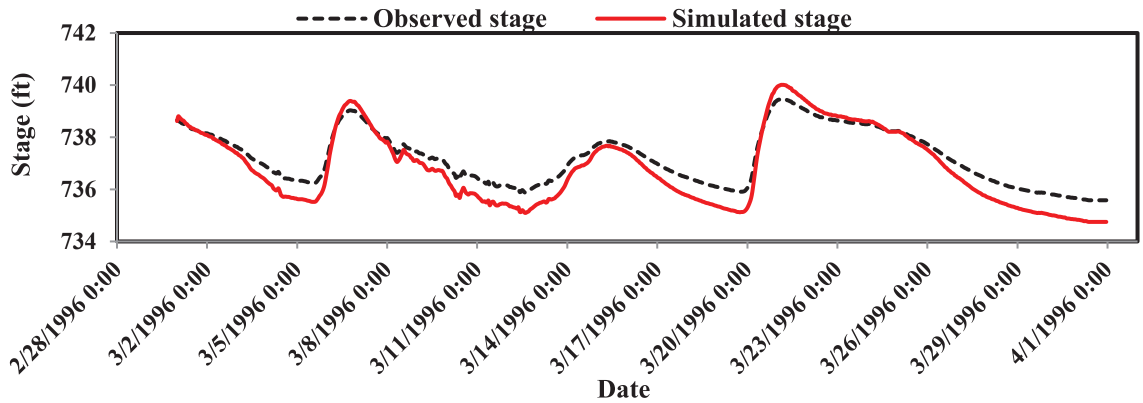


Figure 3-2: Flowchart of overall modelling approach



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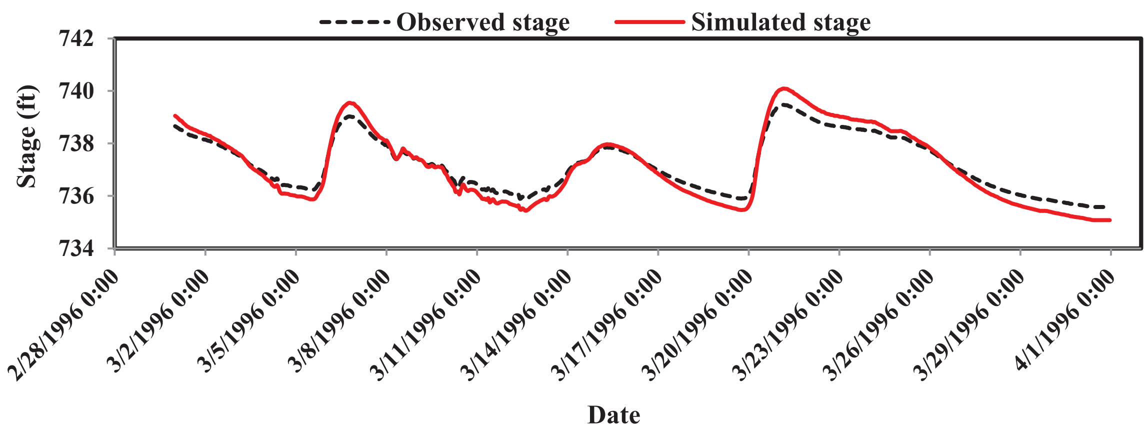

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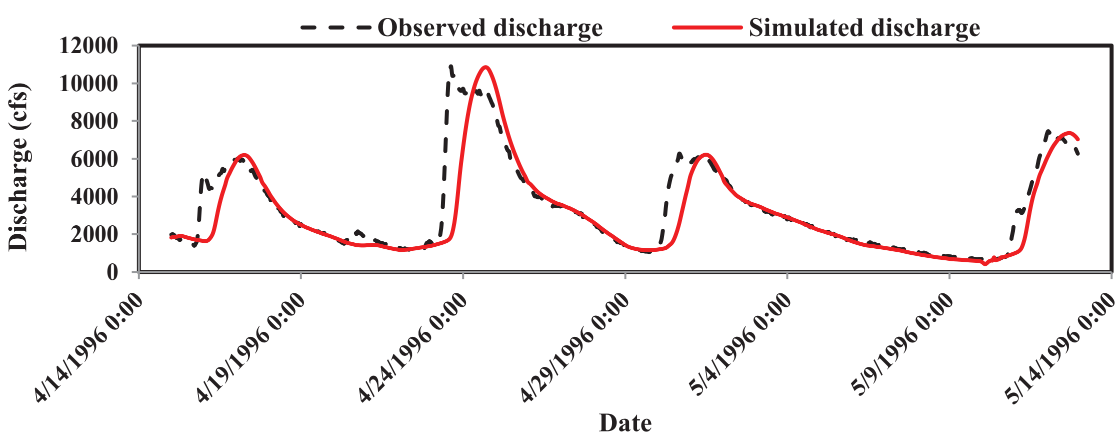
Figure 3-3: Stage calibration of 1D model (a), 2D model (b), from 1996(3-01 to 3-31) at upstream station (Harpersfield-04211820)



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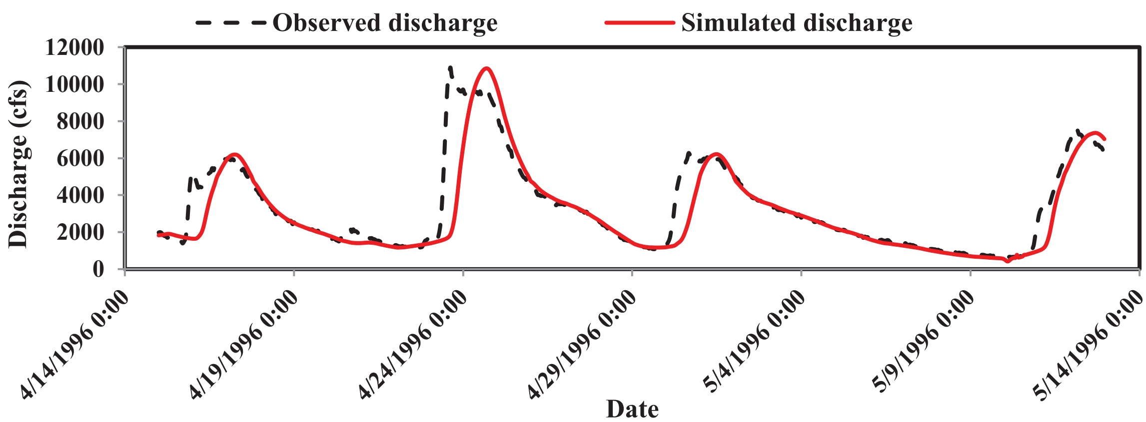

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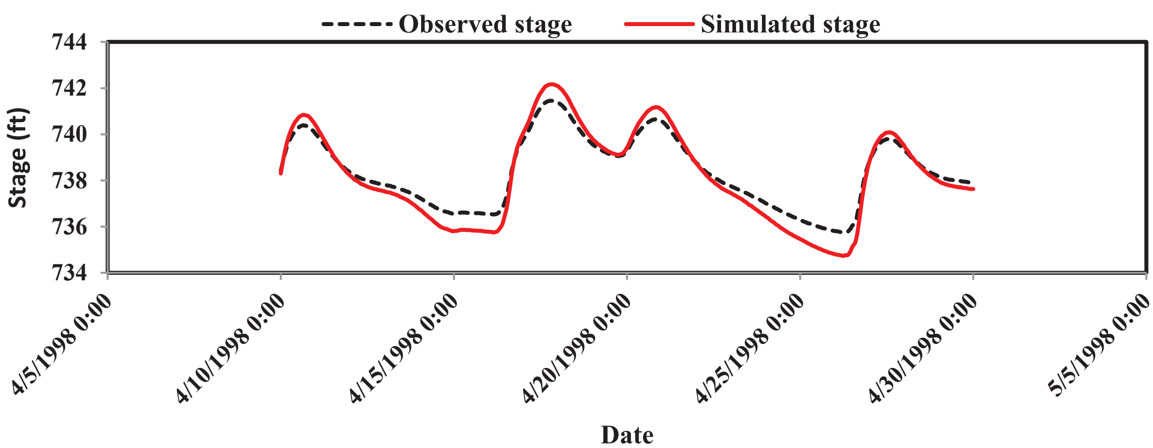
Figure 3-4: Discharge calibration of 1D model (a), 2D model (b), from 1996(4-15 to 05-12) at downstream station (Painesville -04212100))



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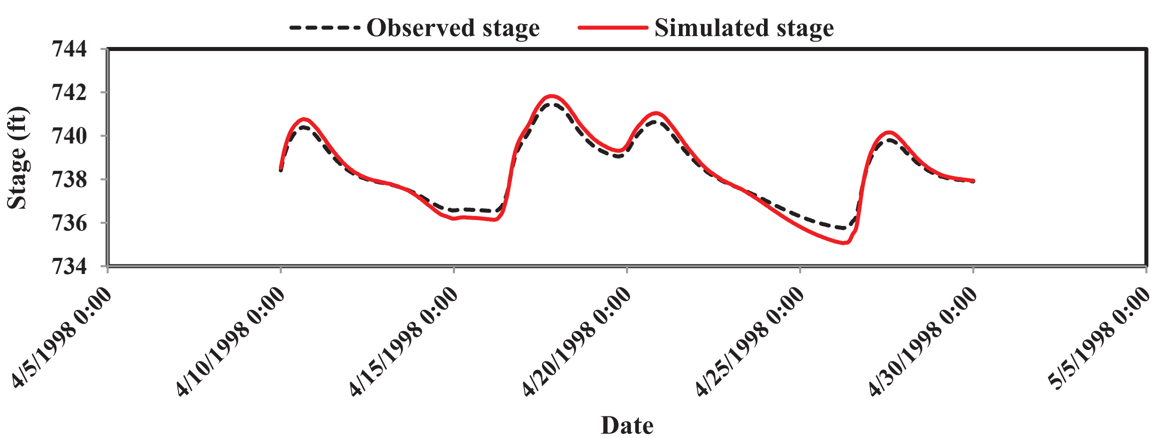

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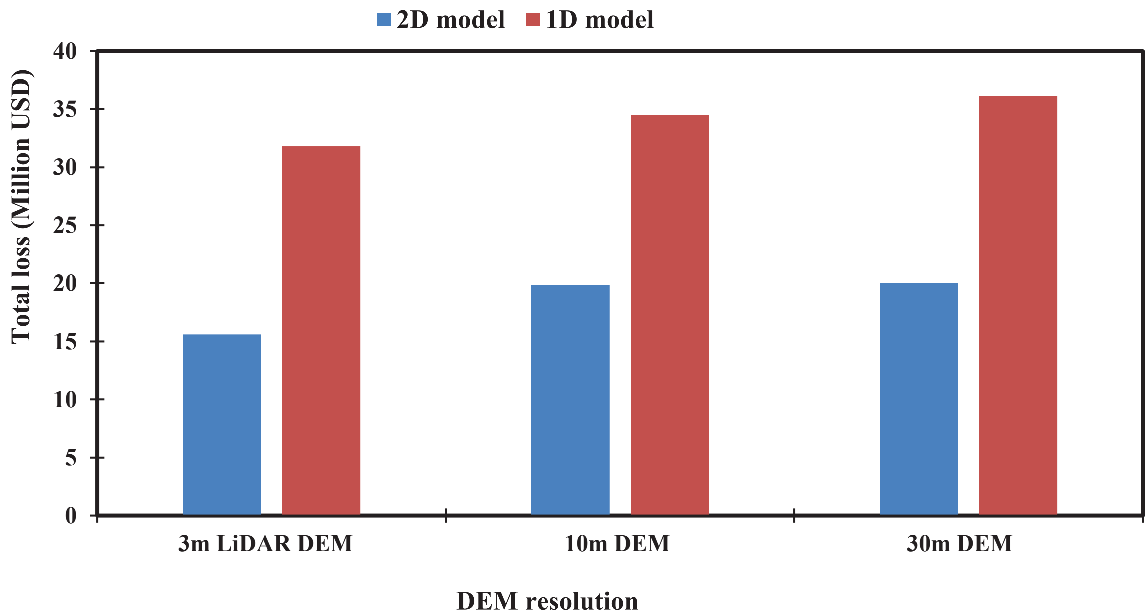
Figure 3-5: Validation of the 1D model (a), 2D model (b), from 1998(04-10 to 04-30)



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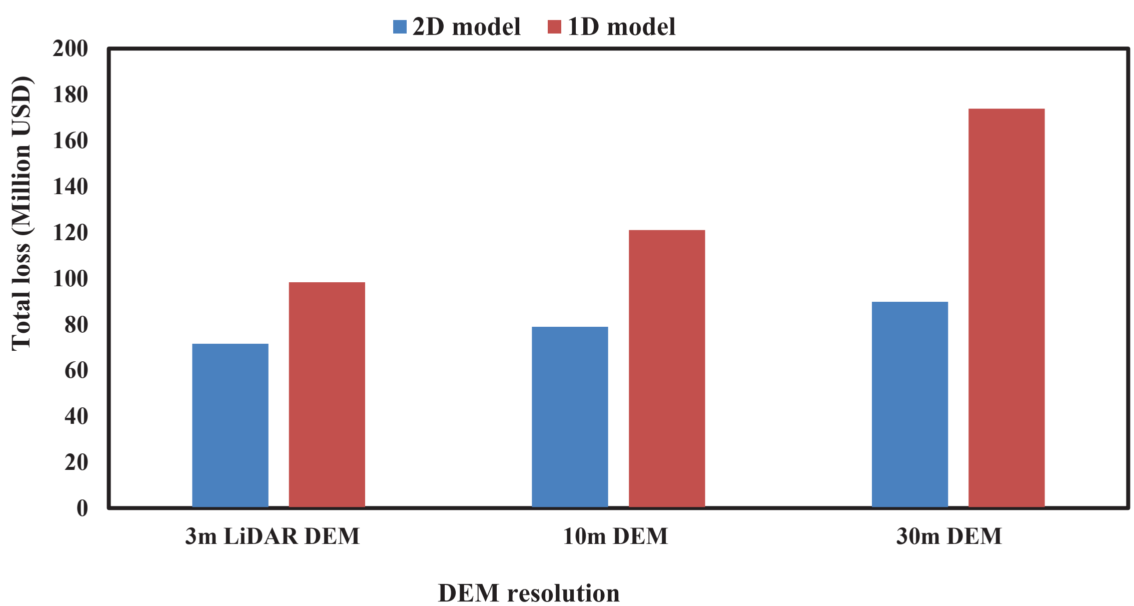

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Figure 3-6: Estimation variation with 1D and 2D modeling techniques with updated inventory (a), with default inventory (b), performed in different topographic resolutions

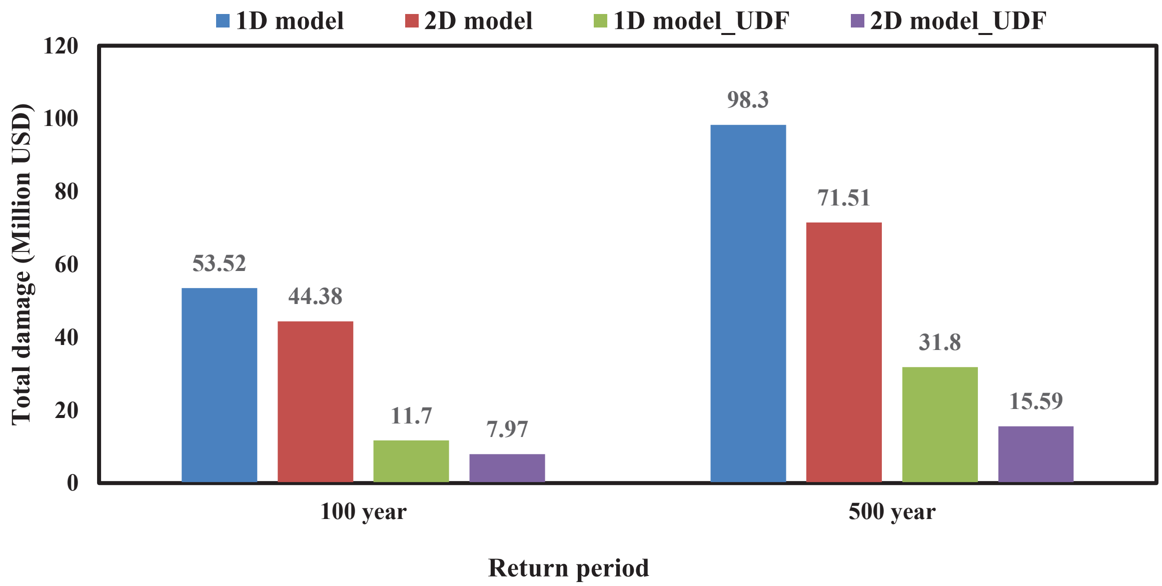


Figure 3-7: Variation in modelling technique within fine resolution LiDAR data

(* UDF= User Defined Facility)

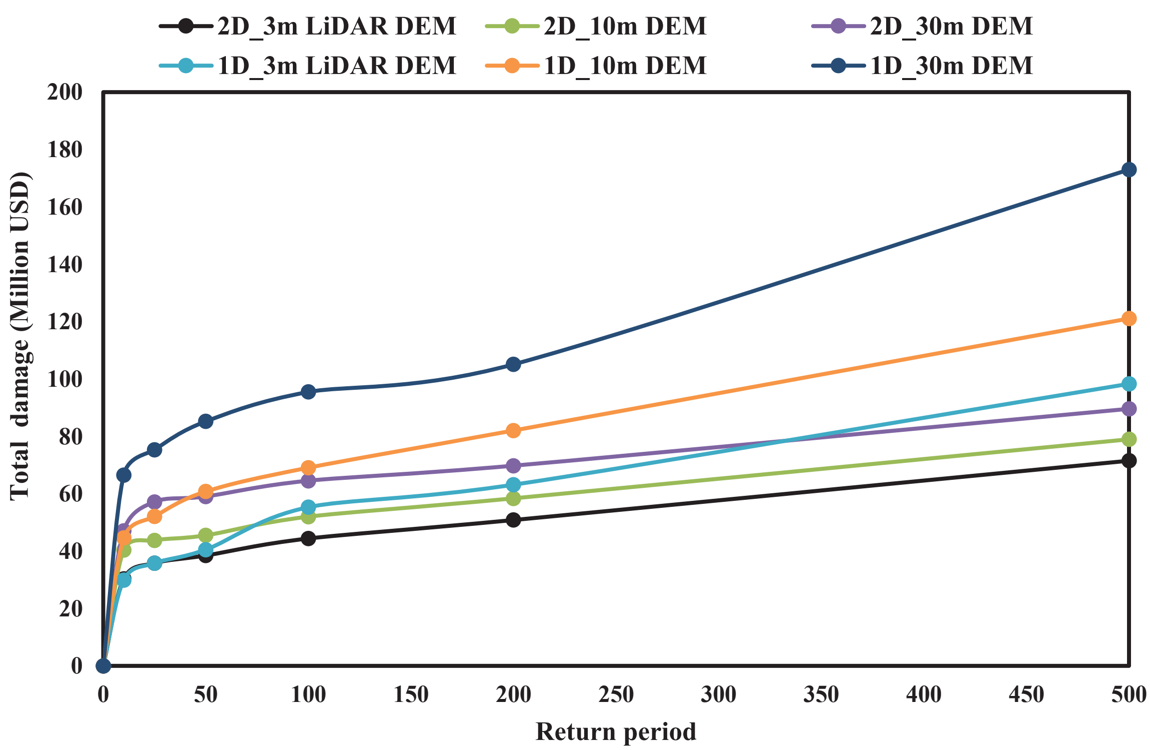


Figure 3-8: Damage versus return period curves for various terrain resolution

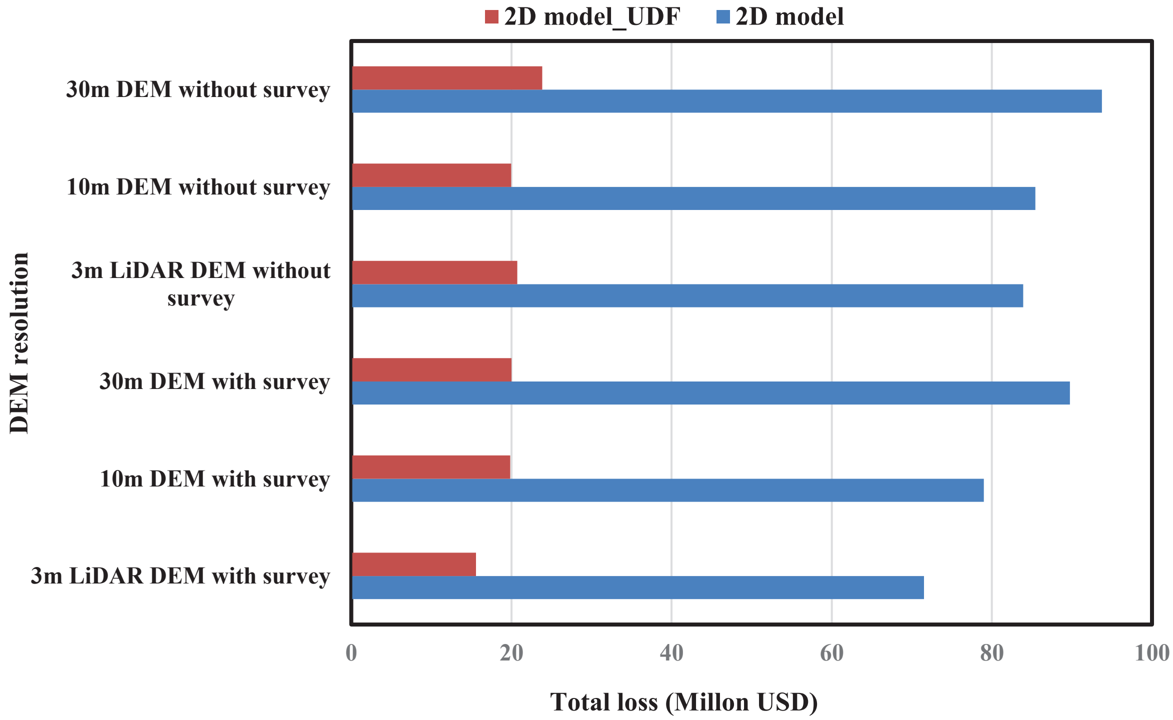


Figure 3-9: Effect of updating inventory data in estimation with 2D model

(* UDF= User Defined Facility)

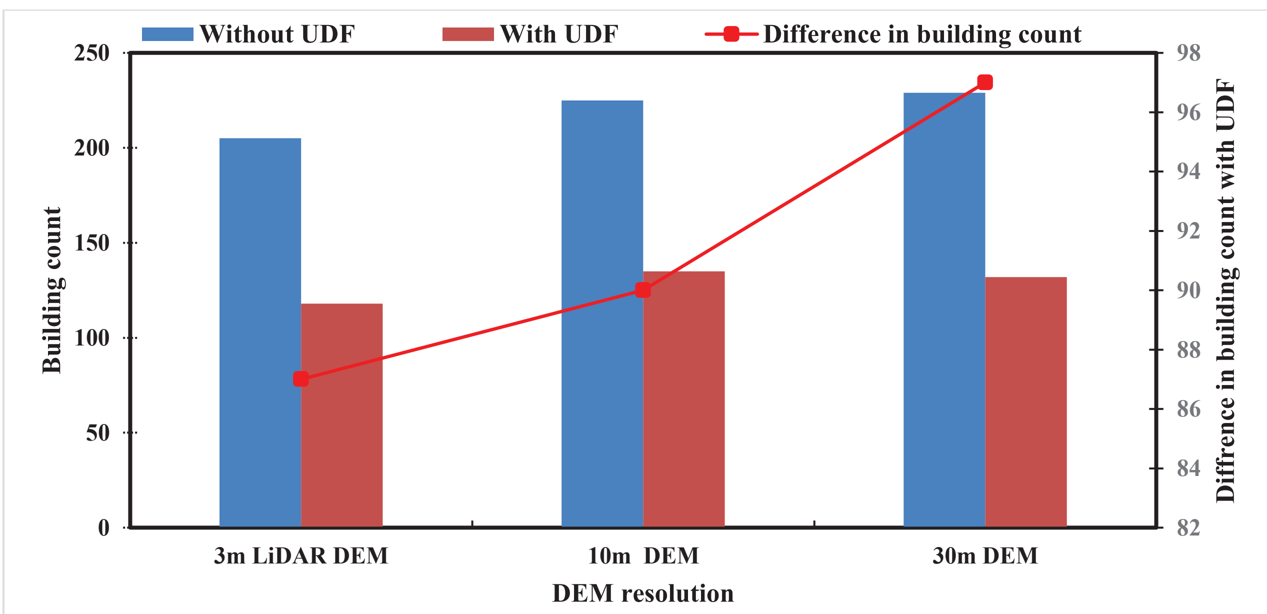


Figure 3-10: Effect of updating inventory data in terms of building damage count in 2D model

(* UDF= User Defined Facility)

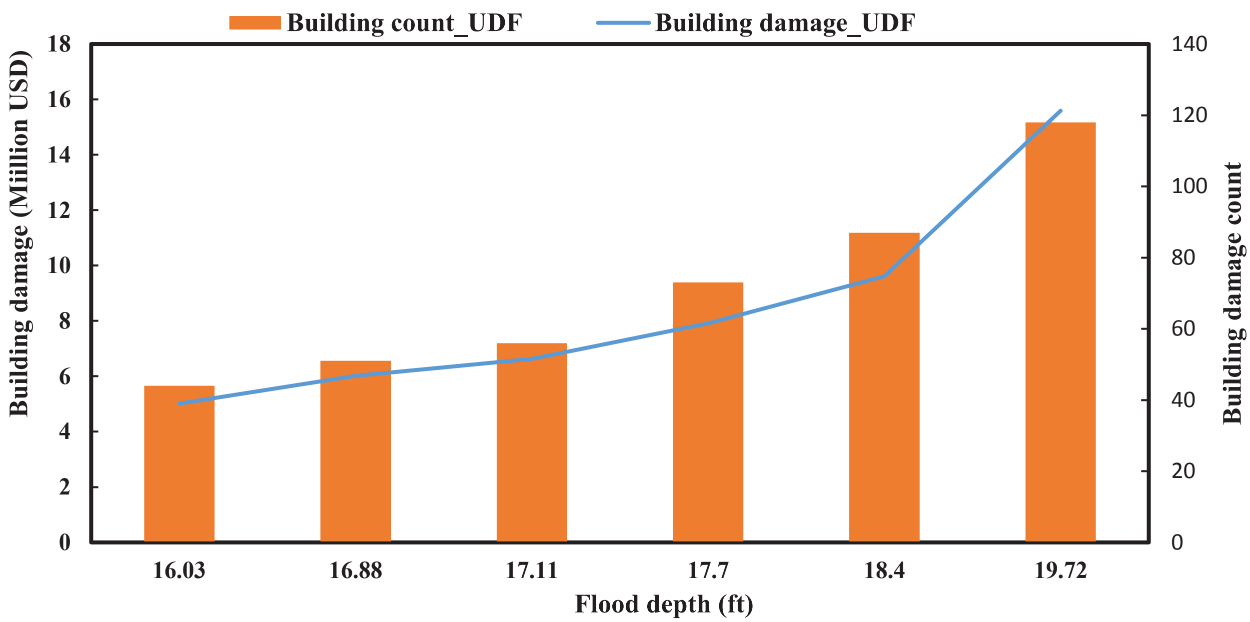


Figure 3-11: Variation of total estimated damage and building count with flood depth

(* UDF= User Defined Facility)

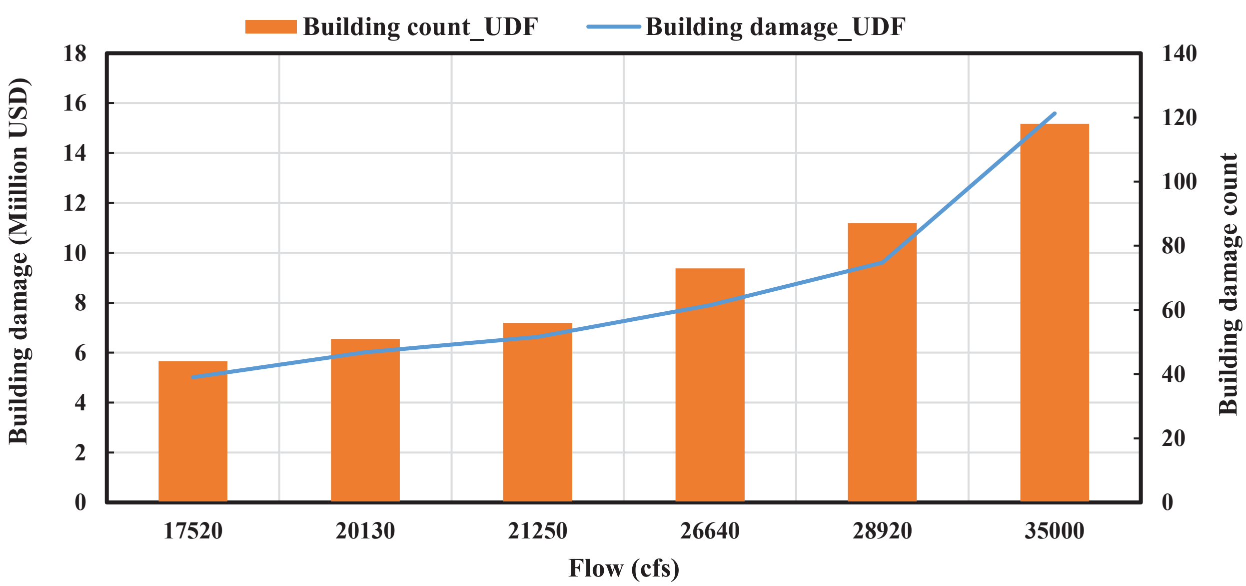


Figure 3-12: Variation of total estimated damage and building count with flow

(* UDF= User Defined Facility)

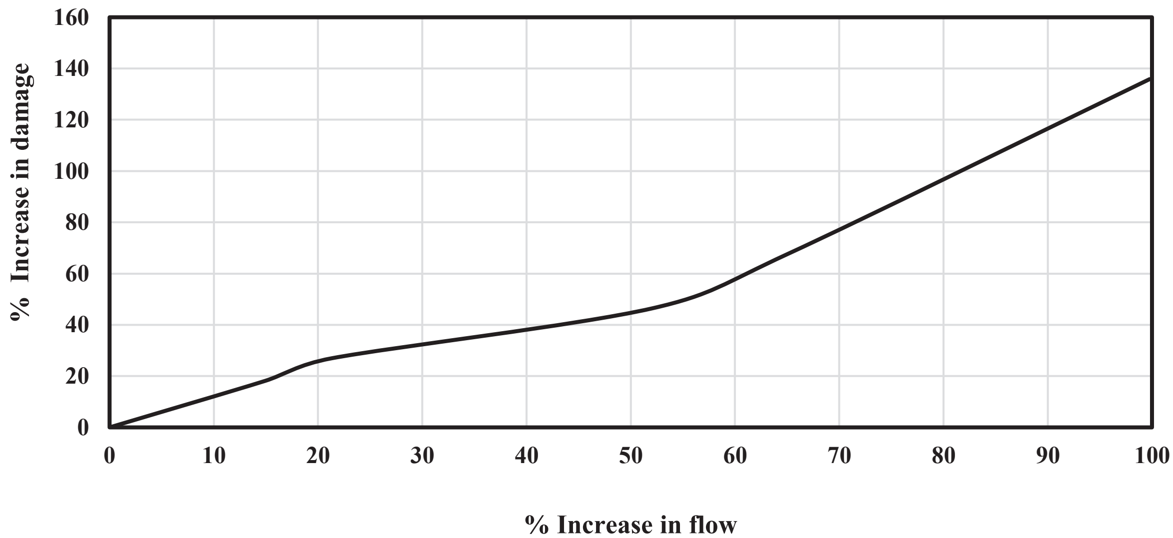


Figure 3-13: Relationship between changes in flow and change in damage estimation

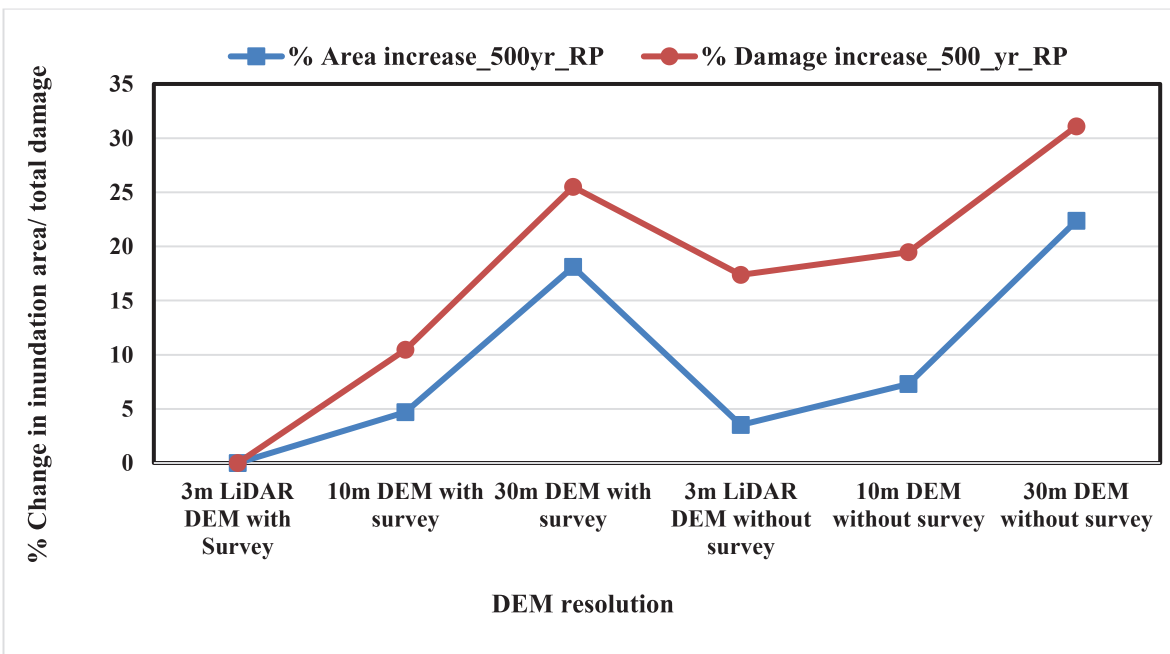
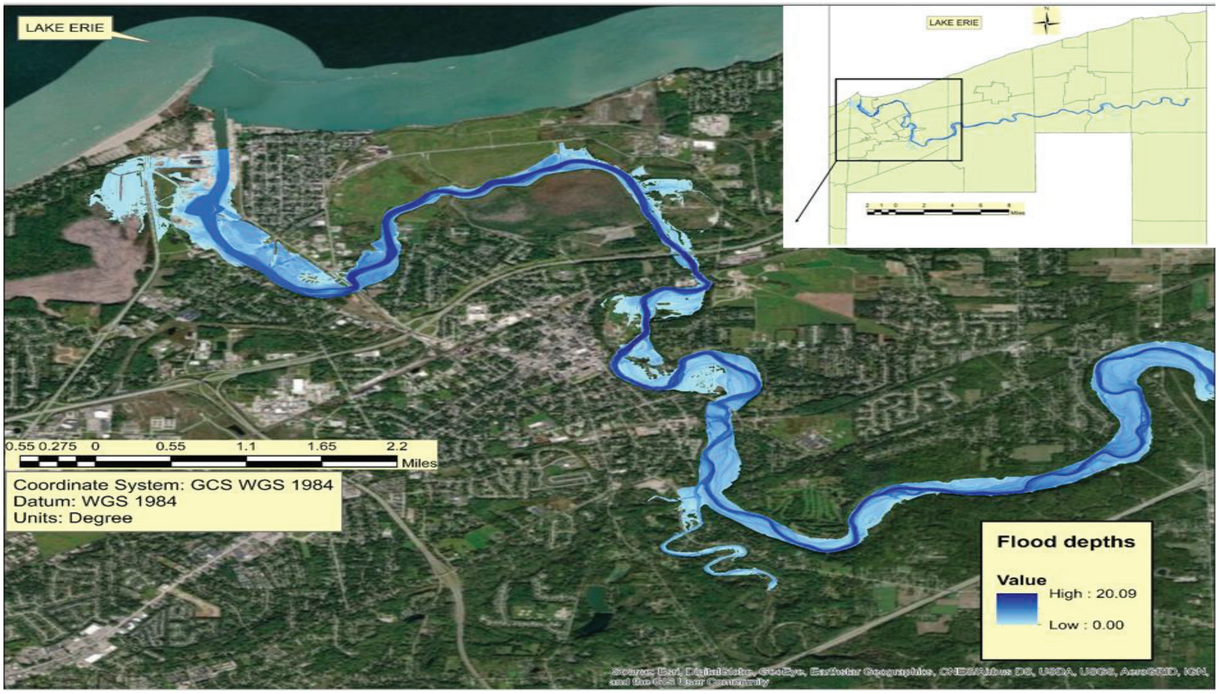
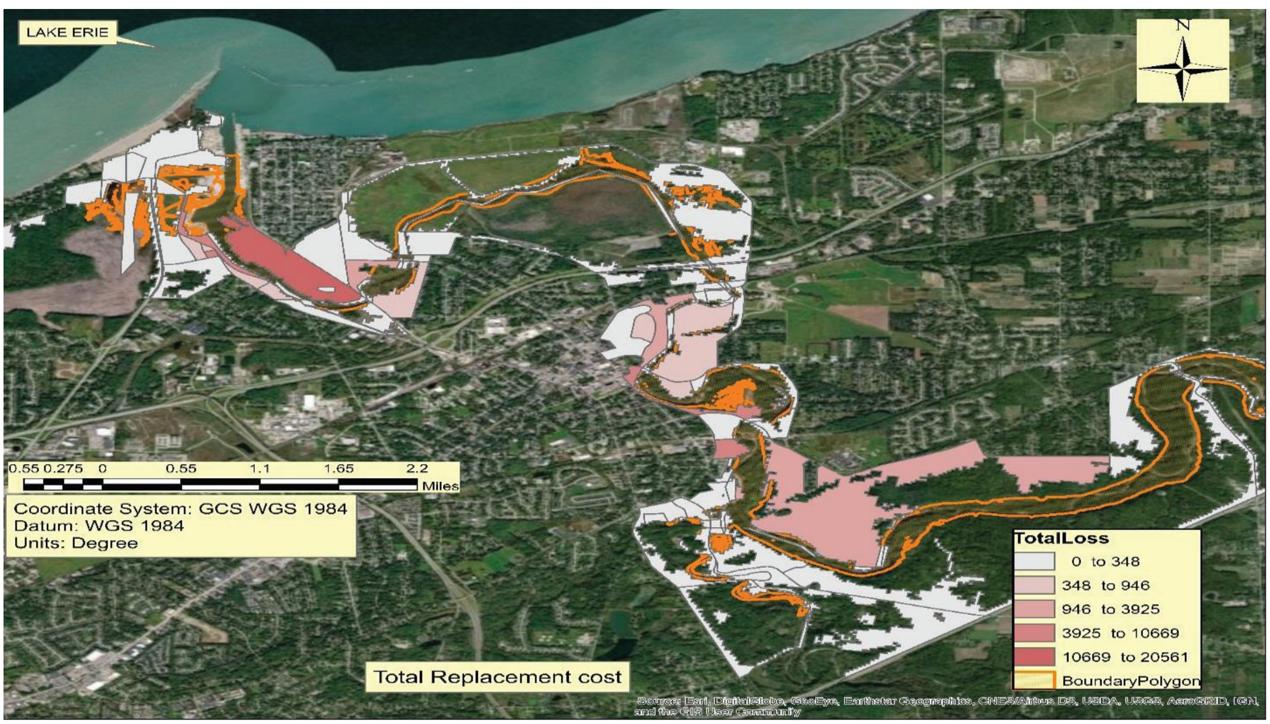


Figure 3-14: Effect of topographic data on inundation area and damage estimation

(* RP= Return Period)



(a)



(b)

Figure 3-15: Flood depth grid (a), and damage map (b), of 2006 flood with total replacement cost of building using 2D HEC-RAS and HAZUS-MH

Table 3-1: Stage calibration/validation of the upstream station (04211820) from 1996 to 1998

Stage calibration at 04211820										
SN	Date		Statistical parameter							
			NSE		R^2		PBIAS		RSR	
	From	To	**1D**	**2D**	**1D**	**2D**	**1D**	**2D**	**1D**	**2D**
1	3/1/1996 0:00	3/30/1996 0:00	0.74	0.90	1.00	1.00	0.05	0.01	0.51	0.31
2	4/15/1996 0:00	5/12/1996 23:00	0.84	0.92	1.00	1.00	0.00	-0.02	0.39	0.28
3	10/20/1996 0:00	11/28/1996 23:00	0.84	0.92	1.00	1.00	0.03	-0.01	0.40	0.29
4	2/4/1997 0:00	2/10/1997 23:30	0.83	0.91	1.00	1.00	0.02	-0.02	0.41	0.30
Stage validation at 04211820										
5	2/26/1997 0:00	3/3/1997 23:30	0.81	0.92	1.00	0.99	-0.07	-0.05	0.43	0.28
6	3/5/1997 0:00	3/19/1997 23:30	0.82	0.84	1.00	1.00	0.00	-0.03	0.43	0.40
7	5/15/1997 0:00	6/6/1997 23:00	0.85	0.94	0.99	0.98	0.02	0.01	0.39	0.25
8	4/10/1998 0:00	4/30/1998 0:00	0.89	0.96	1.00	1.00	0.02	-0.01	0.33	0.21

Table 3-2: Discharge calibration/validation of the downstream station (04212100) from 1996 to 1998

Discharge calibration at 04212100										
SN	Date		Statistical parameter							
			NSE		R^2		PBIAS		RSR	
	From	To	**1D**	**2D**	**1D**	**2D**	**1D**	**2D**	**1D**	**2D**
1	3/1/1996 0:00	3/30/1996 0:00	0.74	0.75	0.88	0.89	11.04	11.01	0.51	0.5
2	4/15/1996 0:00	5/12/1996 23:00	0.72	0.74	0.86	0.88	9.18	9	0.53	0.51
3	10/20/1996 0:00	11/28/1996 23:00	0.9	0.91	0.96	0.96	8.85	9.02	0.31	0.29
4	2/4/1997 0:00	2/10/1997 23:30	0.84	0.87	0.92	0.94	1.26	1.33	0.4	0.36
Discharge validation at 04212100										
5	2/26/1997 0:00	3/3/1997 23:30	0.33	0.4	0.7	0.73	5.2	4.97	0.82	0.78
6	3/5/1997 0:00	3/19/1997 23:30	0.69	0.74	0.85	0.88	7.37	7.45	0.56	0.51
7	5/15/1997 0:00	6/6/1997 23:00	0.8	0.81	0.92	0.92	-3.34	-3.68	0.45	0.44
8	4/10/1998 0:00	4/30/1998 0:00	0.83	0.86	0.92	0.93	3.24	3.21	0.41	0.38