Incorporating the Effect of DEM Resolution and Accuracy for Improved Flood Inundation Mapping

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Abstract

Topography plays a major role in determining the accuracy of flood inundation areas. However, many areas in the United States and around the world do not have access to high quality topographic data in the form of Digital Elevation Models (DEM). For such areas, an improved understanding of the effects of DEM properties such as horizontal resolution and vertical accuracy on flood inundation maps may eventually lead to improved flood inundation modeling and mapping. This study attempts to relate the errors arising from DEM properties such as spatial resolution and vertical accuracy to flood inundation maps, and then use this relationship to create improved flood inundation maps from coarser resolution DEMs with low accuracy. The results from the five stream reaches used in this study show that water surface elevations (WSE) along the stream and the flood inundation area have a linear relationship with both DEM resolution and accuracy. This linear relationship is then used to extrapolate the water surface elevations from coarser resolution DEMs to get water surface elevations corresponding to a finer resolution DEM. Application of this approach show that improved results can be obtained from flood modeling by using coarser and less accurate DEMs, including public domain datasets such as the National Elevation Dataset and Shuttle Radar Topography Mission (SRTM) DEMs. The improvement in the WSE and its application to obtain better flood inundation maps is dependent on the study reach characteristics such as land use, valley shape, reach length and width. Application of the approach presented in this study on more reaches may lead to development of guidelines for flood inundation mapping using coarser resolution and less accurate topographic datasets.

Keywords: Flood Inundation Maps; Topographic Datasets; DEM Resolution; HEC-RAS; DEM Accuracy

1 **Introduction**

2 According to the U.S. National Weather Service, floods account for an average of 89 deaths and
3 property losses up to \$8.2 billion per year in the United States. Flood risk areas in the U.S. are
4 usually identified using the flood inundation maps provided by the Federal Emergency
5 Management Agency (FEMA). Even though these maps use the best available technical data to
6 identify flood prone areas, they have varying level of uncertainties (Aycock & Wang, 2004;
7 Merwade et al., 2008; Wang & Zheng, 2005). These uncertainties arise from one or more
8 sources, including topography data, discharge measurements, choice of model, model
9 assumptions, and model parameters (Hall et al., 2005; Jung & Merwade, 2011; Lin et al., 2012;
10 Pappenberger et al., 2005; Pappenberger et al., 2006; Rayburg et al., 2009; Srinivas et al., 2008;
11 Straatsma & Huthoff, 2011; Werner et al., 2005). Among these various uncertain sources,
12 topography has been reported to be one of the major contributors to the overall accuracy of flood
13 inundation maps (Bates et al., 2003; Brandt, 2005; Cook & Merwade, 2009; Tate et al., 2002).

14 Generally, topography data in the form of a Digital Elevation Model (DEM) are used in creating
15 a hydraulic or hydrodynamic model, and in mapping the flood inundation extent. With the
16 growing availability of LiDAR (Light Detection and Ranging) data in many states in the U.S.,
17 DEMs derived from LiDAR are increasingly used in the delineation of flood inundation areas.
18 The horizontal resolution and the vertical accuracy associated with LiDAR data are significantly
19 better compared to the old DEMs derived from contour surveys, cartography, photogrammetry,
20 interferometry and radar imaging. For example, a LiDAR derived DEM can have horizontal
21 resolution of as high as 0.5 m, and the reported vertical accuracy is in the range of 0.15 to 0.25 m
22 (Aguilar et al., 2010; Giglierano, 2010; Smith, 2010). On the other hand, the vertical accuracy of

old DEMs can range anywhere from 2 to 22 m (Gesch, 2007; Li & Wong, 2010; Rutter et al., 2010). As a result, the flood inundation maps derived from LiDAR are much more accurate compared to the maps derived by using any other available topographic datasets in the world (Casas et al., 2006; Charlton et al., 2003; Schumann et al., 2008).

While the flood maps derived by using LiDAR are accurate, collecting LiDAR data is very expensive. In the U.S., LiDAR data are available for less than 40 percent of the continental states (Snyder, 2012). LiDAR data derived from high point density elevation measurements or smaller post-spacing increase the survey costs and computational time considerably due to handling of vast amount of data, higher sensor pulse rates, and lower flight altitudes (Aguilar et al., 2010; Raber et al., 2007). While the U.S. and other developed regions in the world have resources to collect LiDAR data, many regions in the world depend on coarser resolution, less accurate DEMs derived from Shuttle Radar Topography Mission (SRTM) and Interferometric Synthetic Aperture Radar (IfSAR) for creation of flood inundation maps (Sanders, 2007). The question this study is attempting to address is: how can the accuracy of flood inundation maps derived from coarser DEMs be improved in the absence of any better topographic information such as from LiDAR?

Two key attributes or properties of a DEM, including the horizontal resolution and the vertical accuracy, are important in flood inundation mapping (Gallant et al., 1997; Haile et al., 2005). Many studies in the past have focused on understanding the importance of DEM resolution in flood inundation mapping and have concluded that higher resolution DEMs produce more accurate flood maps when compared to coarser resolution DEMs which over-predict the flood extents (Brandt, 2005; Cook & Merwade, 2009; Werner, 2001). Specifically, for the same

1 vertical accuracy, a coarser resolution DEM will produce higher flood inundation extent. The
2 vertical accuracy of a DEM is affected by its source, sampling techniques and interpolation
3 techniques (Bater & Coops, 2009; Burrough, 1986; Chaplot et al., 2006; Heritage et al., 2009;
4 Merwade, 2009; Smith et al., 2004). Studies based on comparative analysis of vertical accuracy
5 of DEMs have concluded that LiDAR datasets have the least vertical error when compared to
6 other available DEMs used for hydraulic modeling such as the United States Geological Survey
7 (USGS) National Elevation Dataset (NED 10 and NED 30), Interferometric Synthetic Aperture
8 Radar (IfSAR), Advanced Spaceborne Thermal Emission and Reflection (ASTER), Composite
9 DEM (CODEM) and Shuttle Radar Topography Mission (SRTM) (Gonga-Saholiariliva, 2011;
10 Heritage et al., 2009; Hodgson et al., 2003; Schumann et al., 2008).

11 In order to model and remove DEM errors, many studies have focused on identifying the spatial
12 distribution of vertical errors and developing error distribution surfaces (Hodgson & Bresnahan,
13 2004; Höhle & Höhle, 2009; Hu et al., 2009; Stal et al., 2011). Recent error distribution models
14 have focused on dividing the errors into theoretical form, which includes errors due to data
15 capture and empirical form, which includes errors due to information loss (Aguilar et al., 2010).
16 Some models have used geographically weighted regression equations derived from terrain
17 parameters to create a single multivariate model for the entire study area suggesting a localized
18 dependence on terrain parameters (Carlisle, 2005; Erdoğan, 2010). Even though both these
19 models provide a better representation of the spatial distribution of DEM errors, their accuracy is
20 highly dependent on the sample size of the observed data and can produce unrealistic values of
21 elevations for certain regions. As a result, the application of error surfaces created using these
22 models to correct topographic datasets for use in hydraulic modeling is tedious and unreliable
23 (Wise, 2011; Yue et al., 2007).

1 If DEM errors cannot be removed completely using theoretical or regression models, then
2 techniques to reduce the impact of these errors on flood mapping need to be developed.
3 Similarly, while the effect of DEM resolution and vertical accuracy on flood inundation maps is
4 well studied, an attempt to incorporate this knowledge in improving the quality of flood
5 inundation maps is needed.

6 The overall goal of this paper is to improve the quality of flood inundation maps by rectifying
7 the error induced by the DEM resolution and accuracy. This goal is accomplished by addressing
8 the following specific objectives: (1) develop a relationship between flood inundation area and
9 DEM properties such as horizontal resolution and vertical accuracy; (2) create flood inundation
10 maps from low quality (coarser horizontal resolution and/or low vertical accuracy) DEMs by
11 incorporating the relationship developed in the first objective; and (3) compare the improvement
12 in flood inundation maps developed in (2) with the ones developed using LiDAR for the same
13 areas. These objectives are satisfied by creating multiple topographic datasets through
14 resampling and error analysis, and using these datasets to produce flood inundation maps for six
15 stream reaches in the U.S.

16 **Study Area and Data**

17 Six stream reaches in the U.S., as shown in Figure 1, are used in this study. These reaches are
18 chosen based on varying reach length, slope, geographic and climate settings, impervious cover
19 and land use characteristics to provide a range of attributes to study the effect on hydraulic
20 modeling. Among these six reaches, the Iowa River reach is primarily used for validation of
21 results obtained by using the other five reaches. Strouds Creek is a tributary of Eno River in
22 North Carolina, and it is the smallest reach with an urban floodplain, V-shaped valley and history

of high floods. The meandering Tippecanoe River reach near Winamac, Indiana has a highly developed floodplain with commercial and residential buildings. The St. Joseph River reach near Elkhart, Indiana has urban land use, U-shaped valleys and highly developed floodplain. The city of Elkhart has experienced many flood disasters in the past including some major ones in 1908, 1950, 1982 and 1985. The East Fork White River reach near Bedford, Indiana, is a tributary of the Wabash River, and is surrounded by industrial and agricultural areas. The main channel is surrounded by trees and natural vegetation which act as natural levees for restricting flow into the floodplain. The Clear Creek reach in Iowa, which is used for validation, has shallow main channel and flat terrain with cities of Oxford and Coralville situated within its floodplain. The Brazos River reach in Texas is the largest reach with a shallow main channel and meandering bends. The study area around this reach has recorded major floods in the past which led to the provision of levees around the main channel.

Hydraulic modeling for all study reaches is performed by using 100-year return period flow. A high flow value is chosen because the floodplains for the large study reaches do not get inundated for smaller return period flows. The 100-year flow values for Tippecanoe River, Clear Creek, St. Joseph River and East Fork White River are obtained by fitting the Log-Pearson III distribution (Bulletin 17b method) to the annual peak flow series at the corresponding USGS gaging stations. The 100-year flow for the Brazos River reach is provided by the Fort Bend County in Texas, and the flow data for Strouds Creek is provided by the North Carolina Floodplain Mapping Program (NCFMP). Details about the study reaches including the geometry data, 100-year flow values, LiDAR DEM resolution, slope and sinuosity are presented in Table 1. Additional topographic datasets used for Strouds Creek, Brazos River and East Fork White

River study areas include NED 30 m and SRTM 90 m DEMs that are available from USGS (NED: <http://ned.usgs.gov/> and SRTM: <http://earthexplorer.usgs.gov/>).

Methodology

To accomplish the three objectives listed in the Introduction section, the methodology includes the following steps: (i) resampling of DEM data to create topographic datasets with varying horizontal resolutions; (ii) introduction of errors corresponding to coarser resolution and vertical accuracy into the resampled DEMs; (iii) flood modeling and inundation mapping using HEC-GeoRAS and HEC-RAS; (iv) development and validation of the relationships between the DEM properties (horizontal resolution and vertical accuracy), and flood inundation map extent. Figure 2 shows the LiDAR DEMs with cross-sectional configuration for the reaches used in this study.

Resampling of Topographic datasets

The high resolution LiDAR DEMs for all study areas are resampled into coarser resolution DEMs by using the nearest neighbor resampling technique in ArcGIS. The original 6 m resolution LiDAR for Strouds Creek is resampled into DEMs of grid sizes ranging from 9 m - 100 m. Similarly, the original 3 m resolution LiDAR DEMs for Tippecanoe River, St. Joseph River, East Fork White River and Brazos River are resampled into DEMs of grid sizes ranging from 6 m - 100 m. Among the study areas, Clear Creek reach in Iowa is excluded from resampling because this reach is used for validation of the results from this study.

Introduction of DEM errors

Two types of errors are considered in this study including those arising from resampling of a DEM from a finer to coarser resolution, and those arising from data sources (e.g., measurement error). The error related to resampling can be estimated by computing Root Mean Square Error (RMSE) for each of the resampled raster with respect to the original LiDAR DEM in order to report a single global elevation error statistic for the entire DEM (Fisher & Tate, 2006). All resampled DEMs will have this error. DEM accuracy measurements standards provided by the National Standards for Spatial Data Accuracy (NSSDA) state that the DEM errors follow a normal distribution which is a fair assumption for an open terrain with residual errors lying within 95% confidence intervals (Aguilar et al., 2007; FGDC, 1998; Flood, 2004). To create a normally distributed error surface, the mean and standard deviation of the errors are needed. The RMSE of the resampled DEMs for each study area is used as the mean, and the standard deviation is computed by taking the difference in elevations between resampled DEMs and LiDAR DEM. This error raster is then added to all resampled DEMs using ArcGIS Spatial Analyst toolbox to represent raster datasets that have both resampling and vertical errors.

Hydraulic modeling and flood inundation mapping

After incorporating resampling and/or vertical errors, all resampled raster datasets are then used to create a 1D HEC-RAS (USACE, 2010) model by using HEC-GeoRAS (Ackerman, 2009) tool in ArcGIS. HEC-RAS is the most commonly used flood modeling tool in the United States. *The use of a 1D model for simulating the 100-year flow is justified because during such high flow conditions, both the main channel and the floodplain are completely inundated with no storage areas in the floodplain and the entire floodplain acts as a single channel. All simulations are conducted by assuming a steady-state, which is typical for simulating the 100-year design flow in*

1 *practice*. The HEC-RAS models for all the reaches were previously calibrated and used for
2 creating the 100-year flood inundation maps so the boundary conditions and Manning's n values
3 in these models are used without any modification. The HEC-RAS parameters are kept
4 unchanged for different DEMs because the goal is to investigate the sensitivity of inundation
5 maps to topographic errors instead of trying to create a new calibrated model for each
6 topographic dataset. After HEC-RAS simulations, the output files are imported into ArcGIS
7 using HEC-GeoRAS for creating flood inundation maps.

8 9 *Development of relationships between DEM attributes and Hydraulic Outputs*

10 Once the flood inundation maps for all raster datasets are obtained, the average water surface
11 elevation and the inundation area corresponding to each raster input are computed. The water
12 surface elevation and the inundation area obtained from DEMs of different resolutions and
13 vertical errors are then regressed against DEM cell size to establish a relationship between DEM
14 size (resolution) and hydraulic outputs. Finally, the relationships that are developed between
15 DEM attributes and hydraulic outputs are validated by investigating whether the flood inundation
16 maps developed from coarser resolution DEMs can be improved by using this information.

17 **Results**

18 In order to analyze the results, the study reaches are classified into two groups based on the land
19 use and size of the reach. Group A includes Strouds Creek, Tippecanoe River and St. Joseph
20 River, which are relatively smaller reaches surrounded by urban areas. Group B includes East
21 Fork White River and Brazos River, which are relatively large reaches surrounded by
22 agricultural areas. Generally the flood losses are higher in urban areas compared to

1 rural/agricultural areas. Similarly, the flood extent is larger for larger river reaches compared to
2 smaller reaches. Putting the data into these broad groups will provide a context to look at the
3 relative impact of topography on hydraulic outputs for the study reaches.

4 *Error from resampling of DEMs*

5 After the DEMs are resampled into different resolutions, RMSE is computed for each DEM with
6 respect to the LiDAR DEM. RMSE for all river reaches included in the study increases with
7 decreasing DEM resolutions as shown in Figure 3. The magnitude of RMSE is found to be
8 related to the slope of the terrain and the size of the study area. For example, Strouds Creek had
9 the largest RMSE of 0.69 m for a 24 m DEM compared to that for Tippecanoe River (RMSE =
10 0.44 m) and St. Joseph River (RMSE = 0.38 m). The difference between predicted elevations
11 using a LiDAR and coarser resolution DEMs decreases for larger reaches with relatively flat
12 terrain as shown by a smaller RMSE (0.24 m) for a 24 m DEM for East Fork White River and
13 Brazos River (RMSE = 0.25 m). The RMSE has a linear relationship with grid size ($R^2 > 95\%$)
14 which suggests that DEM resolution has a significant effect on the accuracy of topographic
15 datasets. The RMSE for a 9 m DEM for Strouds Creek is 0.34 m as compared to 0.80 m for a 30
16 m DEM which is a significant decrease in the accuracy of the dataset due to resampling.

17 The slope of the linear trend lines for the reaches presented in Figure 3 suggest that DEM errors
18 are higher in magnitude for Strouds Creek, which has urban land use with high spatial variability
19 of elevations when compared to larger reaches with agricultural land use. The linear trend lines
20 also suggest that the effect of coarser resolution DEMs on vertical accuracy is relatively smaller
21 for larger reaches with flat terrain.

Effect of DEM Resolution on Hydraulic Outputs

The water surface elevations for all cross-sections within a reach are averaged to produce one mean water surface elevation (WSE) for a specific DEM resolution. Tables 2 and 3 present the effect of DEM resolution on hydraulic model outputs including mean WSE and inundation area for reaches in Group A and B, respectively. Figure 4 shows the relationship between mean WSE and DEM resolution for Strouds Creek, Tippecanoe River and St. Joseph River; whereas Figure 5 shows the relationship between mean WSE and DEM resolution for East Fork White River and Brazos River.

The mean WSE increases linearly with grid size for Strouds Creek, Tippecanoe River and St. Joseph River. For example, the average water surface elevation for Strouds Creek increases about 0.8 m and 2.96 m for the 30 m and 100 m resolution DEM respectively when compared to the 6 m LiDAR DEM. Similarly, the inundation area increases linearly with DEM grid size. The area of inundation increases about 13.8% (60 m DEM) and 42.6% (100 m DEM) for Tippecanoe River, 7.6% (30 m DEM) and 22% (100 m DEM) for St. Joseph River when compared to the 3 m LiDAR DEMs. Overall, the regression equations between hydraulic outputs and grid size have an R^2 greater than 90% for the three study reaches in Group A suggesting a very good linear fit.

The inundation area is higher with a coarser resolution DEM compared to a finer resolution DEM for the same number of inundated cells. As the DEM resolution becomes coarser, the smoothening of the elevations raises the overall surface, which in turn leads to higher water surface elevations and flood inundation extents (see Figure 4). The percentage change in inundation is more for Strouds Creek with a small size and V-shaped valley when compared to St. Joseph River which has a U-shaped valley to route more flow through the river than the

1 floodplain. The effect of valley shape on the WSE and flood inundation extent is visible in
2 Figure 6 that shows one typical cross-section for each study reach. For two similarly sized
3 reaches, it would be reasonable to assume that as the DEM gets coarser, the results from a U
4 shaped valley to be similar from a V shape valley because the shape gets smoother with coarser
5 resolution. The results from Strouds Creek are more pronounced in this study because it is much
6 smaller compared to the St. Joseph River.

7 The effect of surrounding topography and valley shape is also visible for the White and Brazos
8 River. The change in mean WSE and inundation area for a 100 m DEM of East Fork White
9 River is relatively small in comparison to the results from the original 3 m LiDAR DEM due to
10 its deep U-shaped valley and a highly elevated floodplain which causes most of the flow to be
11 routed through the main channel (see Figure 5 and 6). In the case of Brazos River, the flat terrain
12 and shallow main channel causes most of the water to flow through the floodplain. As a result, a
13 0.5 m increase in mean WSE for the 100 m DEM causes an 18.26% increase in the inundation
14 area. The hydraulic outputs and DEM resolution have a linear relationship ($R^2 > 90\%$) for both
15 East Fork White River and Brazos River. These results suggest that the linear relationship holds
16 true for all study reaches irrespective of the size and land use type.

17 Figure 6 also shows how the top width and water depth changes when the DEM resolution is
18 changed for all reaches. As mentioned earlier, the increase in WSE with coarser grid size is
19 mainly caused by the increase in the channel bed elevation from the smoothening effect due to
20 DEM resampling. This in turn causes the top width of the channel sections to increase with grid
21 size, thus directly affecting the flood inundation extent. For small study areas like Strouds Creek
22 and Tippecanoe River, the channel bed is not accurately represented by coarser resolution DEMs
23 and therefore, there is a significant loss in the topographical information from DEM resampling.

For large rivers like Brazos River, the loss in topographic features is less significant due to the larger width of the cross-sections. The inundation extents for the study areas produced using DEMs of different grid sizes are presented in Figure 7, highlighting the impact of DEM resolution on the quality of flood inundation maps.

Effect of DEM Errors on Hydraulic Outputs

Hydraulic modeling is also performed by using DEMs that are coarser and have vertical errors arising from other sources such as measurement errors. The results presented in Figure 8 show flood inundation area is again linearly related to the vertical error. The slope of the linear fit between mean WSE and vertical error is steeper compared to the fit between DEM resolution and WSE. This is expected because these DEMs have both the resampling error and the vertical error. Strouds Creek is the most affected reach among all the study reaches, and it shows an increase of 3.6 m in the average WSE and 113% increase in the inundation area from a 80 m DEM compared to the original 6 m LiDAR DEM.

The inundation area for Strouds Creek slightly decreases for 9 m, 12 m, 18 m and 21 m DEMs containing errors as shown in Figure 8. This can be attributed to the random nature of normally distributed errors which can cause significant variation in the topography for smaller cell sizes resulting in large number of spikes in elevation. These spikes create depressions leading to a decrease in predicted area of inundation. However, these variations are very small in magnitude, thus the overall effect of error addition results in an increase in the magnitude of the predicted hydraulic outputs. Addition of error also leads to a loss in channel bed's longitudinal profile for coarser DEMs due to the large magnitude and standard deviations of these errors, thus reducing the accuracy of prediction and quality of flood maps as shown in Figures 9 and 10.

The results of the linear regression analysis for the five river reaches, presented in Figures 4, 5 and 8, show that within a specific range of grid size, the mean WSE and flood inundation area have linear relationships with DEM resolution and vertical error. The question then is: can these linear relationships be exploited to improve hydraulic model outputs and flood inundation areas where only coarser resolution DEMs with high vertical errors are available? This question is explored in the next section.

Validation of linear relationship between DEM attributes and hydraulic model outputs

If linear relationships exist between DEM attributes (resolution and error) and mean WSE, it is possible that this relationship can be extrapolated to get WSE for any specified grid size or vertical error. Whether or not such an extrapolation will give better flood inundation maps from coarser resolution DEMs is tested in this section. Three different combinations of DEM attributes and sources are considered for validation. In part (i), a coarser resolution 30 m LiDAR DEM for Clear Creek without any measurement error is used to account for only errors due to horizontal resolution. In part (ii), a coarser resolution 30 m LiDAR DEM for Strouds Creek with additional measurement error is used to account for errors due to both horizontal resolution and vertical accuracy. In part (iii), two USGS NED 30 m resolution DEMs for East Fork White River and Strouds Creek along with two SRTM 90 m resolution DEMs for Strouds Creek and Brazos River are used to account for errors due to horizontal resolution, vertical accuracy and source of datasets.

(i) Validation using coarser resolution DEMs without measurement error

1 The goal of this validation is to see if a 30 m DEM is available for Clear Creek, can it give
2 results are that are comparable to the results from a LiDAR DEM. First, linear relationships for
3 all cross-sections are developed between the DEM resolution and WSE for four additional DEMs
4 with grid sizes equal to 48, 60, 70 and 80 m that are created by resampling the 30 m DEM (Table
5 4 and Figure 11). These linear relationships are then extrapolated to estimate WSE corresponding
6 to a 3 m resolution DEM as shown in Figure 11. Sample estimates of WSE obtained using the
7 linear relationship for six cross-section stations are presented in Table 4. A 3 m resolution DEM
8 is used for extrapolation to enable comparison with the results obtained by using the LiDAR
9 DEM at the same resolution. The results of this comparison are presented in Figure 12.

10 Using the same technique, water surface elevations are predicted for Strouds Creek, Tippecanoe
11 River, St. Joseph River, East Fork White River and Brazos River and the results are compared to
12 the LiDAR outputs (see Figure 13). The RMSE in WSE between the extrapolated values by
13 using coarser resolution DEM and those obtained by using the LiDAR are presented in Table 5
14 for all the sites. The water surface elevations for Strouds Creek, East Fork White River, Clear
15 Creek and Brazos River match well with the LiDAR results with no significant outliers. The
16 water surface elevations for Tippecanoe River and St. Joseph River are slightly under-predicted
17 with some outliers. This under prediction can be explained by using the grid size versus WSE
18 plots in Figure 4. During the validation, the linear relationships are essentially developed by
19 using the points corresponding to a grid sizes greater than 30m. As seen in Figure 4 (b-c), these
20 points will create a slightly steeper slope which will result in a under predicted WSE for a
21 smaller grid size. The cause for steeper slope at larger grid size can be attributed to the loss of
22 bathymetry and floodplain details for smaller size reaches. Despite this slight under prediction,

the overall results suggest that this approach can be used to get a better WSE estimate from a coarser resolution DEM thus reducing the effect of DEM resolution on hydraulic modeling.

(ii) *Validation using Coarser Resolution Datasets with vertical errors*

In this validation, additional vertical error is added to the coarser resolution 30 m LiDAR DEM for Strouds Creek by creating and adding an error distribution dataset using the RMSE presented in Figure 3. A linear relationship is developed and extrapolated to get WSE at a smaller resolution DEM. Sample results for Strouds Creek are shown in Figure 14. The RMSE of predicted water surface elevations using a 30 m resampled DEM with error is reduced from 5.37 m to 0.68 m using the new approach and the water surface profile is comparable to that from LiDAR results for Strouds Creek. Figure 14 shows the comparison in the water surface elevations and water surface profiles for the 30 m DEM containing errors, predicted profile using the new approach and the LiDAR (base) results for Strouds Creek.

The validation results presented until now used a coarser resolution DEM that is created by resampling a finer resolution LiDAR DEM. The quality of these DEMs is relatively better compared to what one would get from public domain such as from USGS NED or SRTM datasets. Will the validation results be different if a public domain DEM such as a 30 m DEM from USGS or 90 m SRTM DEM is used? This is verified in the next section.

(iii) *Validation using Public Domain Datasets*

In this section, the validation is carried out by using two public domain datasets, USGS 30 m NED and SRTM 90 m DEM. It is assumed that the public domain datasets have errors from both

1 being coarse and source errors arising from measurements, interpolation techniques and
2 information loss. First, the error associated with both the NED and SRTM datasets is computed
3 in the form of RMSE by using the LiDAR datasets for Strouds Creek, White River and Brazos
4 River. Next, the 30 m NED and 90 m SRTM DEMs are used to create coarser resolution DEMs
5 through resampling and linear propagation of DEM errors. This is done by evaluating the RMSE
6 for these datasets by selecting a set of points in the floodplain and using the linear relationship of
7 RMSE with grid size to create normally distributed error datasets which are added to resampled
8 coarser resolution DEMs. These modified datasets are then used to develop linear regression
9 equations, which are then extrapolated to estimate WSE corresponding to a finer resolution
10 DEM. These WSE estimates and the WSE that one would get by using just the 30 m NED and 90
11 m SRTM DEMs are then compared to the results obtained from LiDAR as shown in Figure 15.

12 The WSE estimates obtained through extrapolation of linear relationship are significantly better
13 compared to that from just using the public domain DEMs. The WSE is improved by 40% in
14 terms of RMSE for East Fork White River and by 36% for Strouds Creek. The improvement is
15 even more substantial for the SRTM DEM. For example, the WSE estimates improved by 51%
16 for Brazos River and 65% for Strouds Creek. This analysis suggests that the initial quality of
17 topographic datasets and existing error also impacts the accuracy of the WSE results obtained
18 using the linear regression. For Strouds Creek, a 30 m resampled DEM (RMSE = 0.8 m) derived
19 from LiDAR data produces better WSE estimates using this approach than a 30 m NED DEM
20 (RMSE = 1.5 m) and a 90 m SRTM DEM (RMSE = 4.6 m).

Summary and Conclusions

Topographic datasets play a significant role in hydraulic modeling and the accurate prediction of flood inundation areas. Even though LiDAR data are highly accurate, hydraulic modeling and flood inundation mapping is still carried out using datasets obtained from other sources that are less accurate due to the cost in obtaining LiDAR data. DEM resolution and error are two main attributes that affect the hydraulic modeling results, and many studies have concluded that flood inundation mapping results can be improved using only high quality topographic data. The accuracy of hydraulic modeling using coarser resolution DEMs that are widely available across the globe can be improved using the approach developed in this study if accurate modeling of spatial distributions of DEM errors is carried out. The current methods used for DEM error analysis are too complicated and their application for hydraulic modeling purposes relies heavily on detailed topographic surveys. Therefore, a simpler approach is used in this study which uses normally distributed DEM errors. This study addresses the challenges of hydraulic modeling using low quality data and focuses on using the relationship between DEM attributes and hydraulic outputs to reduce the impact of coarser resolution and vertical errors in DEMs.

The following conclusions are drawn from this study:

1. A comparison of RMSE of resampled topographic datasets with grid size shows that the amount of error increases with decreasing DEM resolution. The five study reaches used in this study show a strong positive linear relationship ($R^2 > 90\%$) between resampling error and grid size.

2. For the same set of boundary conditions and flow, the mean WSE also show a strong positive linear relationship with DEM grid size for all the areas used in the study.
3. The predicted flood inundation areas for all the study reaches increase with decreasing DEM resolution. This suggests that DEMs of coarser resolution over-predict the flood extent. The flood inundation area also shows a strong positive linear relationship with the grid size.
4. The shape of the valleys and channel slope determine the extent to which DEM resampling affects the inundation results. DEM resampling and vertical error introduction has a more significant impact on hydraulic outputs for steeper reaches with V-shaped valleys when compared to flat channel slopes with deeper U-shaped valleys which is evident from the results obtained for Strouds Creek versus East Fork White River.
5. The results also indicate that smaller reaches with higher urban land cover and spatial variability have higher slopes for the linear regression curves. Sites with higher urban cover such as Strouds Creek have steeper regression slopes when compared to Brazos River which has agricultural land cover and a flat terrain.
6. The results from this study are most influenced by the shape and slope of the main channel because of their greater impact on the WSE and inundation area. The terrain and width of the floodplain also influenced the percentage change in hydraulic outputs for different DEM resolutions. Overall, small reaches with steeper channel slope, bank slope and urban land use are influenced more by DEM resolution and accuracy.

1 7. Results from this study show that the linear relationship between the DEM attributes and
2 WSE can be exploited to improve flood inundation maps obtained from coarser and less
3 accurate DEMs. Application of this approach shows that the existing error in the dataset
4 plays a major role in the overall quality of the final result. For example, when a 30 m
5 DEM that is resampled from a LiDAR DEM is used, the results obtained from using the
6 linear regression are much better compared to that from a public domain 30 m NED
7 DEM.

8 8. Further validation using 30 m NED and 90 m SRTM DEM show that the use of
9 regression equation produces significant improvement in WSE estimates. However, the
10 improvement in the WSE and its application to obtain better flood inundation maps is
11 dependent on the study reach characteristics such as its reach length and width.

12 This study provides a methodology for improving hydraulic modeling results and mapping of
13 flood inundation extents in areas where only coarser resolution topography data or DEMs are
14 available. By replicating the methodology presented here, relationships between DEM properties
15 and flood modeling results can be developed, and possibly regionalized. Such regional
16 relationships can be used to improve flood modeling results and create better flood inundation
17 maps where finer resolution DEMs do not exist. Similarly, the methodology presented in this
18 study can also be modified to understand the relationship between the DEM properties and the
19 inundation extent without conducting any hydraulic modeling. For example, for a given water
20 surface, how does the inundation extent changes for different resolution DEMs? If this is known,
21 one could just apply a correction to the hydraulic modeling results to get water surface elevations
22 that may correspond to a better quality DEM.

1 A high resolution LiDAR DEM can provide a very accurate representation of floodplain, but the
2 river bathymetry is still absent in a LiDAR DEM. Inclusion of bathymetry for Tippecanoe River
3 and St. Joseph (results not included) showed the final form of linear relationship is not very
4 different because as the DEM becomes coarser the bathymetry details are lost during resampling.
5 However, the results from using the bathymetry will be better compared to the results from just
6 the LiDAR DEM. Another important consideration is the creation of coarser resolution DEMs
7 through resampling. This study used the nearest neighbor resampling method for resampling all
8 DEMs. If a different method such as bilinear or cubic resampling is used, the results will be
9 slightly different, but not significant. For example, the WSE for Strouds Creek changed by less
10 than 0.1 m when the bilinear or cubic resampling is used.

11 Future work on hydraulic modeling and flood inundation mapping should consider the optimum
12 representation of the spatial characteristics of DEM errors since accurate flood extents can be
13 obtained from WSE by removing DEM errors. Further studies may look into the application of
14 the rating relationships developed between vertical elevation errors and spatial variability by
15 Heritage et al. (2009). *Similarly, more study areas should be examined to establish the validity of*
16 *the relationships developed including arid regions of the western United States. Most flood*
17 *studies in the U.S. and other parts of the world still use HEC-RAS 1D model for flood inundation*
18 *mapping so the results from this study are useful to create improved results in data sparse*
19 *regions. The results from other 1D and 2D hydraulic models may differ from HEC-RAS models*
20 *and further investigation is required to validate the applicability of these results for those*
21 *models. Future studies should include the use of a 2D hydrodynamic model to determine the*
22 *effect of DEM resolution and DEM errors on water surface elevations and flood inundation*
23 *maps.*

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22

1 **Table Captions**

2 **Table 1.** Details of flow and geometry data

3 **Table 2.** Effect of DEM resolution on hydraulic outputs for small reaches with urban land use

4 **Table 3.** Effect of DEM resolution on hydraulic outputs for large reaches with agricultural land
5 use

6 **Table 4.** Validation results for Clear Creek

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9

1 **Figure Captions**

2 **Figure 1.** Layout map of study areas

3 **Figure 2.** LiDAR DEMs with cross-sectional configuration, (a) Strouds Creek; (b) Tippecanoe
4 River; (c) St. Joseph River; (d) East Fork White River; (e) Clear Creek; and (f) Brazos River

5 **Figure 3.** RMSE versus grid size for Strouds Creek, Tippecanoe River, St. Joseph River, East
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7 **Figure 4.** Average WSE and Inundation area versus grid size, (a) Strouds Creek; (b) Tippecanoe
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28 Fork White River USGS; (c) Strouds Creek SRTM; and (d) Brazos River SRTM

Table 1. Details of flow and geometry data

Study Area	DEM Resolution (m)	LiDAR DEM Source	No. of Cross-Sections	100-yr Flow Value (m ³ /s)	Reach Length (km)
Strouds Creek	6	NCFMP	50	103	6.5
Tippecanoe River	3	USGS Indiana Water Science Center	46	366	10.4
St. Joseph River	3	USGS Indiana Water Science Center	52	606	11.2
East Fork White River	3	USGS Indiana Water Science Center	56	3,673	20.2
Clear Creek	1	Iowa Flood Center	86	287	39.0
Brazos River	3	Fort Bend County, Texas	46	3,061	59.9
Study Area	Drainage Area (km ²)	Landuse/Landform	Channel Slope		Sinuosity
Strouds Creek	170	Urban/V-shaped valleys	0.00562		Low
Tippecanoe River	2440	Urban/Shallow meandering valleys	0.00025		High
St. Joseph River	8728	Urban/U-shaped valleys	0.00018		Moderate
East Fork White River	10,000	Agricultural/U-shaped valleys	0.00001		Moderate
Clear Creek	255	Agricultural/U-shaped valleys	0.00079		Low
Brazos River	116,827	Agricultural/Shallow meandering valleys	0.00009		High

Table 2. Effect of DEM resolution on hydraulic outputs for small reaches with urban land use

Strouds Creek				Tippecanoe River				St. Joseph River			
Grid Size	Avg. WSE	Inundation Area	% change	Grid Size	Avg. WSE	Inundation Area	% change	Grid Size	Avg. WSE	Inundation Area	% change
(m)	(m)	(km ²)		(m)	(m)	(km ²)		(m)	(m)	(km ²)	
				3	210.90	2.94	0.00	3	221.28	3.16	0.00
6	164.28	0.36	0.00	6	210.91	2.94	0.17	6	221.32	3.20	1.34
9	164.34	0.37	2.42	9	210.94	2.96	0.68	9	221.33	3.21	1.61
12	164.40	0.39	7.00	12	210.98	2.98	1.31	12	221.47	3.30	4.50
15	164.54	0.39	8.19	15	210.99	3.00	2.05	15	221.41	3.26	3.39
18	164.60	0.40	10.85	18	210.84	2.88	-1.95	18	221.43	3.30	4.48
21	164.74	0.42	15.76	21	211.06	3.01	2.55	21	221.46	3.33	5.55
24	164.82	0.42	15.97	24	211.07	3.05	3.88	24	221.51	3.39	7.46
27	164.94	0.45	23.00	27	211.05	3.05	3.73	27	221.56	3.39	7.48
30	165.07	0.44	21.33	30	211.06	3.03	3.20	30	221.54	3.40	7.65
33	165.19	0.48	32.35	33	211.17	3.10	5.56	33	221.59	3.49	10.56
36	165.35	0.49	35.45	36	211.34	3.24	10.39	36	221.57	3.38	7.23
48	165.79	0.52	43.84	48	211.31	3.24	10.40	48	221.76	3.64	15.35
60	166.31	0.60	66.36	60	211.40	3.34	13.82	60	221.89	3.70	17.18
70	166.67	0.61	68.86	70	211.65	3.56	21.28	70	221.97	3.81	20.59
80	166.75	0.69	89.22	80	211.75	3.79	29.20	80	222.21	3.95	25.16
90	167.29	0.70	93.52	90	212.04	4.26	45.08	90	221.93	3.74	18.47
100	167.24	0.63	74.79	100	212.03	4.19	42.63	100	222.02	3.85	22.04

Table 3. Effect of DEM resolution on hydraulic outputs for large reaches with agricultural land use

Brazos River				East Fork White River			
Grid Size	Avg. WSE	Inundation Area	% change	Grid Size	Avg. WSE	Inundation Area	% change
(m)	(m)	(km ²)		(m)	(m)	(km ²)	
3	22.73	162.29	0.00	3	155.06	18.39	0.00
6	22.73	162.30	0.01	6	155.08	18.42	0.14
9	22.75	164.35	1.27	9	155.08	18.42	0.14
12	22.75	164.44	1.32	12	155.11	18.43	0.22
15	22.77	166.16	2.38	15	155.11	18.43	0.19
18	22.78	166.94	2.87	18	155.12	18.48	0.44
21	22.79	169.25	4.29	21	155.13	18.46	0.36
24	22.81	169.30	4.32	24	155.16	18.49	0.52
27	22.82	170.63	5.14	27	155.18	18.48	0.47
30	22.83	172.39	6.22	30	155.20	18.54	0.82
33	22.84	174.11	7.28	33	155.22	18.57	0.94
36	22.90	177.92	9.63	36	155.24	18.55	0.83
48	22.92	177.58	9.42	48	155.35	18.65	1.40
60	22.98	181.82	12.03	60	155.44	18.80	2.24
70	23.02	184.67	13.79	70	155.58	18.99	3.24
80	23.12	188.51	16.15	80	155.65	18.77	2.03
90	23.07	190.10	17.14	90	155.82	18.93	2.94
100	23.20	191.92	18.26	100	155.84	18.98	3.18

Table 4. Validation results for Clear Creek

<i>Clear Creek*</i>	WSE (m) for different cross-section station (m)					
Grid Size (m)	35738.2	35011.6	17206.2	17191.6	4881.2	174.6
30	228.72	228.95	215.44	215.59	203.16	198.05
48	229.23	229.67	215.53	216.06	204.05	198.90
60	229.21	229.69	216.01	216.44	204.32	198.89
70	229.49	229.66	216.53	216.87	204.92	199.21
80	229.30	229.71	216.68	217.16	205.22	198.85
Slope	0.012	0.014	0.028	0.032	0.041	0.017
Intercept	228.47	228.75	214.45	214.58	201.97	197.79
R²	0.72	0.66	0.91	0.99	0.99	0.60
LiDAR (base)	228.30	228.68	214.74	214.91	203.16	198.75
Predicted (new)	228.49	228.76	214.48	214.61	202.01	197.80

Table 5. RMSE of WSE between extrapolated values by using coarser resolution DEM and those obtained by using the LiDAR

Study Area	Reach Length (km)	RMSE (m)	Avg. Slope
Brazos River	59.9	0.08	0.00009
Clear Creek	39.0	0.66	0.00079
East Fork White River	20.2	0.10	0.00001
St. Joseph River	11.1	0.55	0.00018
Tippecanoe River	10.4	0.26	0.00025
Strouds Creek	6.5	0.75	0.00562

Figure 1. Layout map of study areas

Figure 2. LiDAR DEMs with cross-sectional configuration, (a) Strouds Creek; (b) Tippecanoe River; (c) St. Joseph River; (d) East Fork White River; (e) Clear Creek; and (f) Brazos River

Figure 3. RMSE versus grid size for Strouds Creek, Tippecanoe River, St. Joseph River, East Fork White River and Brazos River

Figure 4. Average WSE and Inundation area versus grid size, (a) Strouds Creek; (b) Tippecanoe River; and (c) St. Joseph River

Figure 5. Average WSE and Inundation area versus grid size, (a) East Fork White River; and (b) Brazos River

Figure 6. Cross-sectional profiles for LiDAR and 100 m DEMs with Elevation (m) on y-axis and Station (m) on x-axis, (a) Strouds Creek; (b) Tippecanoe River; (c) St. Joseph River; (d) East Fork White River; and (e) Brazos River

Figure 7. Comparison of LiDAR and 100 m flood maps, (a) Strouds Creek; (b) Tippecanoe River; (c) St. Joseph River; (d) East Fork White River; and (e) Brazos River

Figure 8. Hydraulic outputs versus grid size comparisons for DEMs containing errors and resampled DEMs (Strouds Creek)

Figure 9. Cross-sectional profiles comparisons for LiDAR and 100 m DEM containing error (Strouds Creek)

Figure 10. Comparison of flood maps between LiDAR and DEMs with errors (Strouds Creek)

Figure 11. Extrapolation of linear regression results for validation (Clear Creek)

Figure 12. Predicted versus LiDAR WSE and water surface profile comparison (Clear Creek)

Figure 13. Predicted versus LiDAR WSE, (a) Strouds Creek; (b) Tippecanoe River; (c) St. Joseph River; (d) East Fork White River; and (e) Brazos River

Figure 14. Comparison of WSE and water surface profile for 30 m DEM with error and predicted results with respect to LiDAR (Strouds Creek)

Figure 15. Predicted and original WSE versus LiDAR WSE, (a) Strouds Creek USGS; (b) East Fork White River USGS; (c) Strouds Creek SRTM; and (d) Brazos River SRTM