

# Impact of Lidar Nominal Post-spacing on DEM Accuracy and Flood Zone Delineation

George T. Raber, John R. Jensen, Michael E. Hodgson, Jason A. Tullis, Bruce A. Davis, and Judith Berglund

## Abstract

*Lidar data have become a major source of digital terrain information for use in many applications including hydraulic modeling and flood plane mapping. Based on established relationships between sampling intensity and error, nominal post-spacing likely contributes significantly to the error budget. Post-spacing is also a major cost factor during lidar data collection. This research presents methods for establishing a relationship between nominal post-spacing and its effects on hydraulic modeling for flood zone delineation. Lidar data collected at a low post-spacing (approximately 1 to 2 m) over a piedmont study area in North Carolina was systematically decimated to simulate datasets with sequentially higher post-spacing values. Using extensive first-order ground survey information, the accuracy of each DEM derived from these lidar datasets was assessed and reported. Hydraulic analyses were performed utilizing standard engineering practices and modeling software (HEC-RAS). All input variables were held constant in each model run except for the topographic information from the decimated lidar datasets. The results were compared to a hydraulic analysis performed on the un-decimated reference dataset. The sensitivity of the primary model outputs to the variation in nominal post-spacing is reported. The results indicate that base flood elevation does not statistically change over the post-spacing values tested. Conversely, flood zone boundary mapping was found to be sensitive to variations in post-spacing.*

## Introduction

Airborne light detection and ranging (lidar) remote sensing has become a widely-used method for acquiring elevation data for trees, shrubs, buildings, and Earth's terrain. Data

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users and vendors commonly referred to these data products as digital surface models (DSMs). The lidar data can be further processed to create bare-earth digital elevation models or DEMs (Jensen, 2000). DEMs are utilized in a variety of geographic applications (Cowen *et al.*, 2000) including hydraulic modeling for flood zone mapping (e.g., Kenward *et al.*, 2000; Marks and Bates, 2000; Manson *et al.*, 2002; Omer *et al.*, 2003). As the DEM is a primary input to this process, it is reasonable to suggest that the accuracy of the DEM surface has an effect on the output of the models and thus the modeled flood extent (often referred to as the *flood zone*).

In 1997, FEMA identified a need to update their database of approximately 100,000 flood insurance rate maps (FIRMs) and therefore initiated the Map Modernization Program (FEMA, 2002 and 2003). As a response to this effort and to the flood damage sustained during the 2000 hurricane season, the State of North Carolina with the support of FEMA undertook a massive project called the North Carolina Floodplain Mapping program to update the FIRMs for the entire state (NCFMP, 2002 and 2003).

Many factors are known to contribute to the accuracy of a DEM derived from lidar data. The nominal post-spacing (or average ground spacing between lidar postings) is believed to be a significant contributor to the overall vertical error prevalent in the lidar-derived DEM (Hodgson *et al.*, 2004). However, unlike other factors that contribute to the overall error budget such as terrain variability and land-cover, post-spacing represents a significant portion of overall project costs. A lower post-spacing generally requires a more sophisticated sensor system with a higher pulse rate, a lower altitude over-flight, a narrower scan angle, or a combination of these variables that results in the need for more flight-lines. In addition, significantly more personnel time and computing resources (processor speed, RAM, mass storage, etc.) are required to process lower post-spacing lidar data.

The goal of this research was to establish an empirical relationship between lidar post-spacing and DEM accuracy within the study area in the piedmont of North Carolina. Further, this research investigated the nature of this relationship on flood zone mapping. This research focused on using established methods and models for statewide mapping efforts currently planned and underway in the United States. Namely, this included the usage of the United States Army Corps of Engineers HEC-RAS and HEC-GEORAS hydraulic model, and the triangulated irregular network (TIN) as the

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data model for digital elevation surfaces. We addressed the following research questions in our study area:

- Does lidar post-spacing affect the vertical accuracy of a DEM?
- Is the flood extent and flood elevation sensitive to changes in DEM accuracy induced by varying lidar post-spacing? Are these sensitivities different under various land-cover and slope conditions?

We tested following directional hypotheses in relation to these research questions:

1. Vertical error in lidar-derived triangulated irregular network (TIN) DEMs varies in a predictable relationship with nominal post-spacing. We expected that the error would decrease as the post-spacing increased.
2. Both the flood elevations and the extent of delineated flood zones are sensitive to changes in post-spacing. Areas that contain higher slopes will exhibit less sensitivity than areas with broader floodplains. We hoped that the results would indicate an optimal nominal post-spacing for use in similar terrain conditions.

## Background

The question of scale has been a central theme in geospatial research for many years (Quattrochi and Goodchild, 1997). Examining a phenomenon or problem at varying scales will often produce different answers based solely on the scale of the examination (Levin, 1992). This has proven to be the case when examining everything from physical features such as the length of a coastline (Mandelbrot, 1967) to various spatial aggregation levels in socio-economic data (Clark and Avery, 1976; Fotheringham and Wong, 1991). Questions related to the issue of scale include: "If I am getting different answers as a function of scale, which answer is correct?" and, "How *sensitive* is my application to changes in scale?" These types of questions become larger issues in certain applications because data may only be available at a particular scale, or costs may be reduced by using a coarser scale. In remote sensing applications, where the trend has always been for data to become available at increasingly finer resolutions, scientists have found that finer resolutions (larger geographic scale) are not always the ideal solution (e.g., Tullis, 2003). When a certain methodology or model that was originally calibrated at a specific scale of analysis is used at a different scale, its utility may decrease.

In this research, we tested scale in the form of lidar post-spacing empirically as it applies to flood mapping. The research attempts to quantify the sensitivity of flood mapping derivatives to an input scale parameter using an emerging remote sensing technology.

The second theoretical concept central to this research is exactly what influences observed error in DEMs, particularly those derived from lidar data. It is important to discuss the current understanding of DEM error sources and the basics of lidar processing to provide a context from which to explain certain unique characteristics of lidar-derived DEMs.

The practical side of this topic has its roots in the effort by various governmental agencies within the United States to assess, plan for, and mitigate flood disasters. Doing this effectively involves accurately predicting future flood conditions.

## Accuracy and Scale in Digital Elevation Datasets

A body of research exists on assessing the vertical accuracy and other derivatives (slope, aspect, etc.) of various digital elevation surfaces. Most of this research has been done over the last 10 to 15 years and is coincident with widespread adoption of digital surfaces in modeling and other GIS applications. Work done relating to the effects of resolution change on DEM accuracy are interesting in the context of this

research, since this is roughly analogous to acquiring lidar data at a larger post-spacing. It is well-established that varying resolutions or scales for a given DEM dataset induces errors in observed accuracy that appear to follow a systematic monotonic pattern: error increases as scale increases. For example, MacEachren and Davidson (1987) found that the observed error in DEM surfaces increased at an increasing rate as the number of samples decreased (i.e., cell size increased). We expected a similar type of empirical relationship in this research. However, the spatial scale being considered in this research is quite different here, as is the introduction of lidar data that brings in other considerations that are discussed later.

## Accuracy in Lidar-derived DEM Surfaces

Overviews of the lidar sensor system for terrain mapping may be found in Jensen (2000) and Maune (2001) and numerous research articles. In this paper only the important elements in the lidar collection and processing approach are highlighted and referenced as they relate to elevation accuracy and surface form accuracy.

In the broadest sense, error in lidar-derived DEM products can be attributed to two non-exclusive general categories, the "system" or the "conditions." The "system" category includes factor sub-groups such as the sensor, the aircraft platform characteristics, interpolation techniques and the data processing algorithm. The "conditions" category includes factor sub-groups such as terrain characteristics, vegetation, and environmental conditions. The accuracy of the DEM derived from lidar data (and derived products like surface slope) is affected by these groups as well as in interaction between these groups. A more detailed discussion of these factors can be found in Hodgson *et al.*, 2005, particularly in the text surrounding Table 1 of that document.

A commonly accepted method to perform an empirical assessment of lidar-derived DEM accuracy is to use the RMSE statistic based on high-grade *in situ* survey spot elevations in the following manner:

$$RMSE_{Observed-DEM} = \sqrt{\frac{\sum (Z_{LIDAR} - Z_{Survey})^2}{n}} \quad (1)$$

A number of studies have empirically assessed the accuracy of DEMs under various conditions. Bolstad and Stowe (1994) examined and then compared the errors associated with a USGS DEM and a DEM derived from a SPOT stereoscopic dataset. Recent research examined error in lidar-derived DEMs as influenced by land-cover and slope (Hodgson *et al.*, 2003 and 2005; Raber *et al.*, 2002).

Some research efforts have specifically focused on this point classification process. Cobby *et al.* (2001) developed an automated segmentation approach for lidar data so that the point-classification algorithm varied by land-cover category. Raber *et al.* (2002) found that vertical accuracy could be improved in lidar derived DEMs if the lidar data was segmented into general land-cover classes prior to processing. Published studies on lidar elevation accuracy often do not include documentation of the point labeling process and the parameter values used since most data vendors regard this as proprietary.

Another factor that is often discussed as affecting accuracy is the interpolation method and/or the data model utilized to create the DEM. For example, Ackerman and Kraus (2004), discuss the relative merits of gridded datasets compared to TINs. Hodgson and Bresnahan (2004) presented an interesting error budget model for a lidar derived DEM surface. By collecting survey elevations at exactly the same

TABLE 1. CHARACTERISTICS OF THE ORIGINAL LIDAR DATASET AND FIVE DECIMATED DATASETS

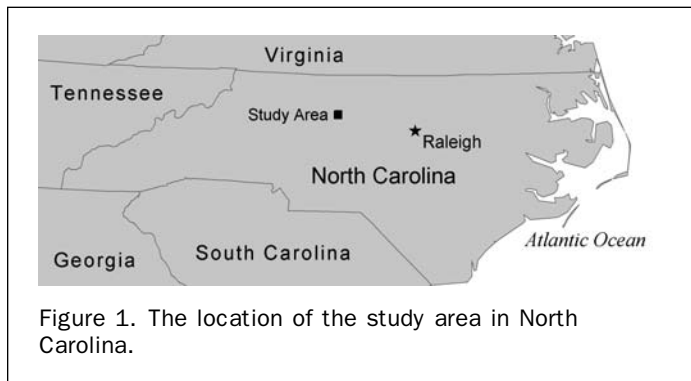
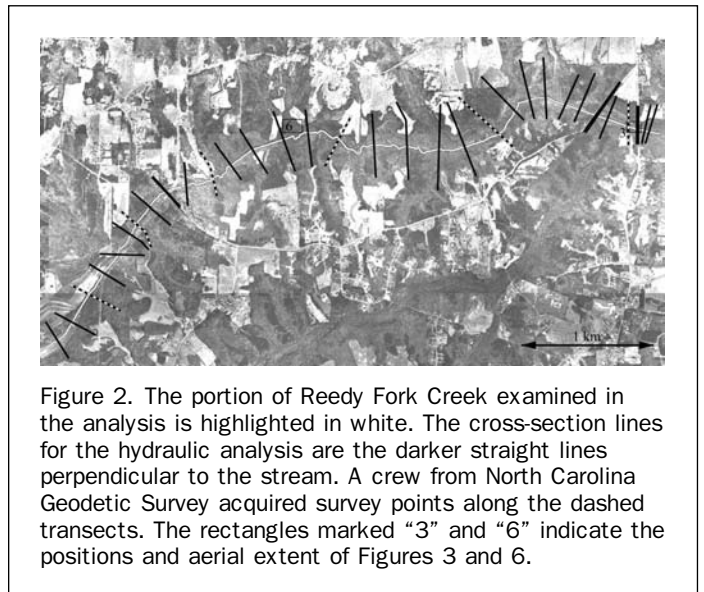
Decimation Level	Average Post-spacing (m) – Before Processing	Average Post-spacing (m) – After Removal of Non-ground Points	Description
0	1.35	1.54	No points removed prior to postprocessing (un-decimated).
1	1.91	2.10	Alternative points along each scan line were decimated, increasing the cross track spacing by a factor of 2. Each scan line was retained.
2	3.86	4.12	Every fourth point along each scan line was retained (increasing the cross track spacing by a factor of 4), and every other scan line was retained (increasing the along track spacing by a factor of 2).
3	5.79	6.28	Every sixth point along each scan line was retained (increasing the cross track spacing by a factor of 6), and every third scan line was retained (increasing the along track spacing by a factor of 3).
4	7.71	8.50	Every eighth point along each scan line was retained (increasing the cross track spacing by a factor of 8), and every fourth scan line was retained (increasing the along track spacing by a factor of 4).
5	9.64	10.80	Every tenth point along each scan line was retained (increasing the cross track spacing by a factor of 10), and every fifth scan line was retained (increasing the along track spacing by a factor of 5).

locations as lidar points, the authors were able to decompose the errors. Their study quantified the contribution of error from the lidar system, interpolation algorithm, terrain slope, land-cover, and reference data.

**Methodology**

**Study Area**

Figure 1 shows the location of the study area in North Carolina. The study area includes approximately 5 km of Reedy Fork Creek downstream from the town of Oak Ridge. The highlighted portion Figure 2 is the study area along Reedy Fork Creek. The area around the stream is mostly rural consisting of pasture and cropland. The area immediately adjacent to the stream is almost exclusively forested hardwood. A number of housing tract developments with large lots are also present.



**Data Acquisition**

Three different types of data were required for this investigation. First, we obtained lidar data were to create the digital elevation models. Second, field crews were dispatched to acquire *in situ* survey x, y, z data to assess the accuracy of the lidar-derived DEM and for hydraulic modeling. Third, ancillary data were required to run the hydraulic model.

**Lidar Data**

The data vendor acquired all lidar data for this investigation in one data collection mission. Although multiple flight

lines were needed to complete the mission over the study area, flight altitude, speed, and sampling intensity remained nearly constant so that nominal post-spacing was similar over the entire study area. This was done because (a) the lidar data collection cost precluded multiple data collection missions, and (b) a single collection of lidar data ensured that the only variable manipulated was post-spacing. Other variables such as weather conditions, GPS error, INS error, and other accuracy issues were assumed to be held constant. We utilized a system of decimation to generate a series of different lidar datasets from the single flight.

The lidar data were initially acquired over the study area on 15 December 2001 (leaf-off conditions) by 3Di, LLC using the Digital Airborne Topographic and Imaging System (DATIS-II). The acquisition altitude was approximately 7,600 feet above ground level (AGL). The pulse rate of the laser was 37,500 pulses per second and the beam size on the ground was approximately 60 cm in diameter. Although the instrument is capable of collecting multiple returns, we only use the final or last return of each pulse for the purposes of this research. This resulted in an approximate average point spacing of 1.35 meters between points. After initial calibration quality control (QC) by a private engineering firm (Eagle View Research), the set of last lidar returns were decimated by retaining only certain points from the original datasets using a specially-designed systematic algorithm (Table 1). This resulted in the creation of five additional simulated lidar datasets with nominal post-spacing ranging from approximately 2 to 10 meters. After the creation of the datasets, at each specified post-spacing, the classification of ground versus non-ground points was also performed on each dataset independently by the contractor using a proprietary algorithm that included some manual editing. The data were processed to a level that represented what would be delivered to a typical lidar data user. Each of the lidar datasets went through the point classification process serially and with no prior or acquired knowledge of specific ground features for manual editing. The creation and processing of the datasets in this manner resulted in “virtual flights.” Table 1 reports the post-spacing of each “virtual flight” at each decimation level. Hereafter, each lidar-derived dataset is referred to as  $D_0$ ,  $D_1$ ,  $D_2$  . . .  $D_5$ . The processed lidar datasets, as described above, were delivered as  $x$ ,  $y$ ,  $z$  comma delimited ASCII text files.

#### Ground Survey Data

The survey crew consisted of licensed surveyors from the North Carolina Geodetic Survey (NCGS) assisted by graduate students. They conducted a traditional ground survey was during the second week of October 2003, to gather cross-sectional information and acquire ground reference information for the accuracy assessment phase of the research. The crew utilized a first-order geodetic control monument that is located in the study area to obtain the real-time differential GPS measurements.

Six cross-sections were surveyed along the length of stream channel (Figure 2). At the start of each of the six cross-sections a foresight and a backsight point were collected using survey grade, real time kinematic (RTK) GPS. The crew verified these points using their relative distance and position calculated using total station survey equipment. Each was found to agree with the RTK measurement to within 1 cm horizontal and 2 cm vertical. In addition, four RTK points were re-measured after a three-week time lag. All re-measured points were within 0.6 cm (both horizontal and vertical) of their original measured values.

The survey crew collected points along each transect at all significant breaks or at a minimum of 6 m. The toe on either side of the stream channel was also collected. However, due to

the small size of the channel (<4 meters across), the channel invert was interpolated and not collected. The toe and bank station marks were not included in the accuracy assessment since lidar returns in these areas, if present, are known to be unreliable due to the presence of water.

After the survey crew delivered the processed survey points, we classified each survey point according to a simple land-cover scheme using a combination of photo-interpretation and field verification. Table 2 contains the land-cover classification scheme with descriptions and photos.

In addition to the surveyed cross-sections, the survey crew collected a number of points under-represented land-cover classes (e.g., pavement and scrub/shrub) bringing the total number of ground survey points to 254.

#### Ancillary Data and Model Preprocessing

The ancillary data required for the hydraulic model included:






- peak flood discharge values for the 25, 50, 100, and 500-year flood,
- corresponding water surface elevations at the downstream end of the study,
- bridge geometry information for the three bridges in the study area,
- the hydraulic roughness coefficients (Manning's  $n$  values), and
- stream bank breaklines.

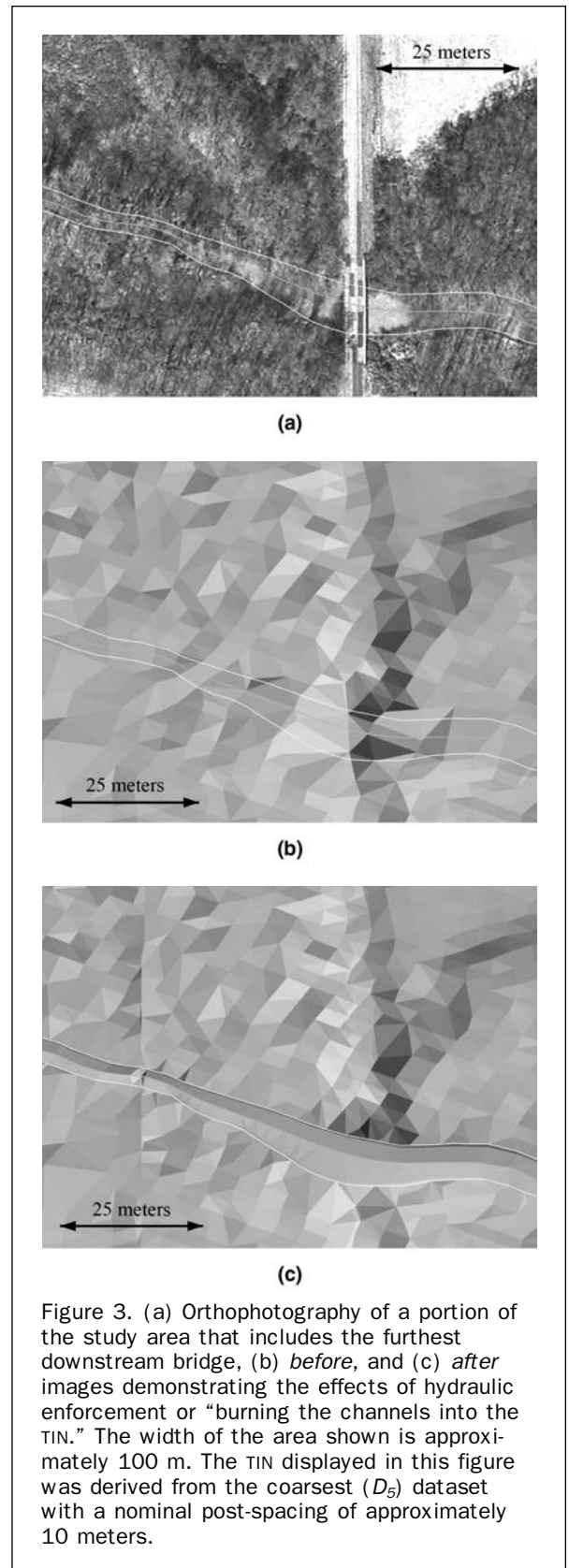
The established USGS regression methods described by Pope *et al.* (2001) for rural piedmont areas in North Carolina were used to derive the peak discharge values for use in the hydraulic analysis were at each cross-section. A stream gauge near the upstream end of the study area has been collecting data since 1956. Estimates of the peak discharge values for return periods 2 to 500 were derived by the USGS from the historical data at this gauge. These estimates agree to within 3 percent of those predicted using the regional regression estimates.

A separate field crew measured the bridge geometry using a sonic measurement device to measure the width of the piers and bridge opening as well as the deck height. These measures were cross-verified using relative measurements acquired from a previous FEMA flood study of the stream in 1989. Unfortunately, current georeferenced survey grade measurements of the bridge opening were not available at the time of study. However, since the hydraulic modeling in this study was applied as part of a sensitivity study, the exactness of the measurements for these types of parameters is less important than keeping them constant between treatments. This also holds true for the roughness coefficients (Manning's  $n$ ), which were taken from the previous study and assigned based on current orthophotography.

The Guilford County GIS Department provided the stream bank breaklines. They were derived from digitization of 1995 orthophotography that was also acquired for use in the study. The location of the stream banks were adjusted based on a compromise between (a) more recent (1998) aerial photography acquired by North Carolina, (b) the undecimated lidar dataset, and (c) the survey measurements of the stream banks at each of the six surveyed cross sections. We assigned elevation values to the breaklines based on the ground surveys and interpolated between surveyed cross-sections. This procedure is often referred to as hydraulic enforcement, or “burning the channels into the TIN.” According to Maune (2003), who describes this process in greater detail, it is necessary to undertake this activity when seeking to extract additional cross sections from a lidar derived DEM. The reason for this is that lidar returns over water are either not present or unreliable, especially in

TABLE 2. LAND-COVER CLASSES USED IN THE ACCURACY ASSESSMENT WITH DESCRIPTIONS

Class and Description	Picture (Specimen in foreground)
<p><b>Pavement</b> Any paved surface (e.g., asphalt or concrete).</p>	
<p><b>Grass</b> Grass or pasture <math>\leq 0.5</math> m in height.</p>	
<p><b>Scrub/Shrub</b> Thick, deciduous growth or chest high weeds with some woody vegetation <math>&lt; 3</math> m. Often a transition class.</p>	
<p><b>Deciduous</b> Forested areas consisting almost exclusively of bottomland hardwood.</p>	
<p><b>Mixed</b> Forested areas containing some conifers.</p>	



shallow water such as in this study area. The process removes all returns within the areas determined to be water, and replaces them with the breakline data. The result of this process is demonstrated in Figure 3. Figure 3 is an area that is approximately  $40 \times 60$  meters centered on the first bridge

in the project area near the third transect from the right on Figure 2. Due to the rolling nature of the terrain and the absence of hydraulically important features (e.g., weirs, dikes, levees, and other flood control measures) no other breaklines were created within the floodplain.

### Data Postprocessing and Hydraulic Model Development

We interpolated a separate surface using each of the lidar datasets (Table 1) as mass points through TIN interpolation. We chose to use TIN interpolation because it is the current standard for hydraulic studies and is required for input into the HEC-GEORAS software (USACE, 2001). The processing required to turn the lidar points classified as ground points into a digital elevation model (DEM) in TIN format is summarized in Figure 4. As mentioned, we used orthophotos to validate the location of the stream bank breaklines. In addition to the stream bank breaklines, the surveyed cross-section cut lines were also utilized as an input for TIN interpolation. The reason for this is so that when the cross-sections are automatically extracted from the TIN as part of the HEC-GEORAS processing the values for that particular cross-section are lifted from the actual survey data rather than the lidar-derived DEM.

The remaining steps in the data process involved executing the hydraulic models and producing a flood zone map for each lidar dataset (Figure 5). First, after consulting with professional engineers, the project team added several additional cross-sections at hydraulically important locations (e.g., flow change, bridge location). The cross-sections were spaced not more than 150 m (500 ft) apart. The average

distance between cross-sections was approximately 100 m with a number being much closer. Once the TINs were created, the geometry at each cross-section was derived in the ESRI ArcView® extension HEC-GEORAS. Those cross-sections not surveyed were taken directly from the TIN surface, as in a detailed or limited detail FEMA study. The resulting set of six differing geometries (one for each lidar dataset) were then imported into HEC-RAS where the hydraulic analysis was performed. All model parameters including the bridge geometry were held constant except for the geometry generated by the TIN surface through each model run.

We then took the output, in the form of water surface elevations at each cross-section, back into GIS software and processed to compute the 100-year flood zone extent. Although the flood elevations for the 25, 50, 100, and 500-year flood were modeled in HEC-RAS, only the 100-year flood zone was determined and analyzed. At this point both sets of data, the flood zone polygons and tabular flood elevations for each level of decimation, used in testing *Hypothesis 2* were created.

Figure 6 is a detailed map of a small portion of the study area showing each of the flood zones created using  $D_0$  (the reference line shown in *black* in each map) and  $D_{1-5}$  (in white displayed separately in Figure 6a through 6e, respectively). By visually inspecting these images, general trends are apparent. The higher decimation levels deviate the most from the reference.

Finally, we used each TIN at the various levels of decimation to determine the elevation value at each of the 254 surveyed points. This information was stored in tabular format for the analysis and testing of *Hypothesis 1*.

### Results

The results of this research are presented in two parts relating to the two stated hypotheses. First, the accuracy assessment portion is presented. Then, the results of the hydraulic sensitivity analysis are described.

#### DEM Accuracy and Post-spacing

The mean absolute error (MAE), as well as the RMSE, values were calculated for the entire set of survey points as well as individually by land cover class (Table 3). Inspection of the values indicates that only a weak relationship appears to be present. In fact, in every forested land-cover class (Deciduous, Mixed and Scrub/Shrub) the error pattern appears random and for *no* categories does the error increase monotonically. However, a general upward trend is apparent in both un-forested classes (pavement and grass).

#### Errors Related to Land-cover

As in previous research, we tested whether or not significant differences in error exist across land-cover (in this case while post-spacing is constant). At each decimation level (simulated nominal post-spacing), this was done using simple one-way ANOVA. The tests were:

$$\text{For } D_0: \text{Elevation Error}_{\text{pavement}} = \text{Elevation Error}_{\text{grass}} \\ = \dots = \text{Elevation Error}_{\text{mixed}}$$

$$\text{For } D_1: \text{Elevation Error}_{\text{pavement}} = \text{Elevation Error}_{\text{grass}} \\ = \dots = \text{Elevation Error}_{\text{mixed}}$$

...

$$\text{For } D_5: \text{Elevation Error}_{\text{pavement}} = \text{Elevation Error}_{\text{grass}} \\ = \dots = \text{Elevation Error}_{\text{mixed}}.$$

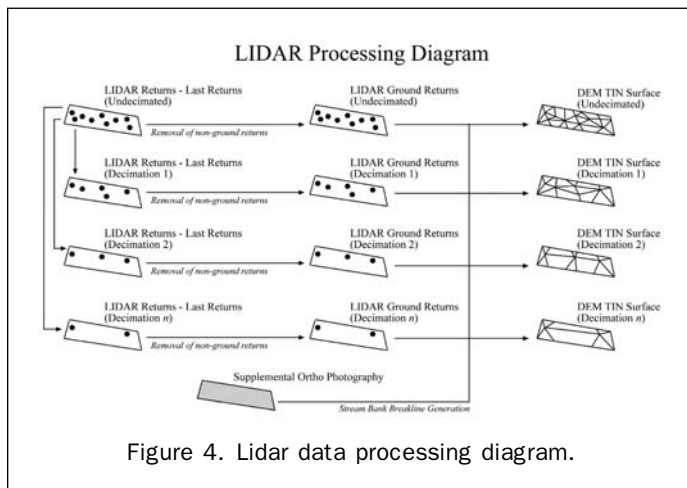


Figure 4. Lidar data processing diagram.

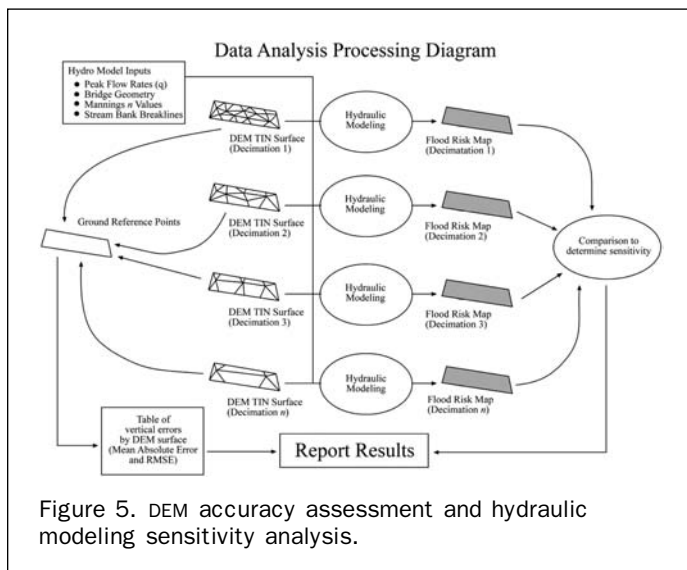


Figure 5. DEM accuracy assessment and hydraulic modeling sensitivity analysis.

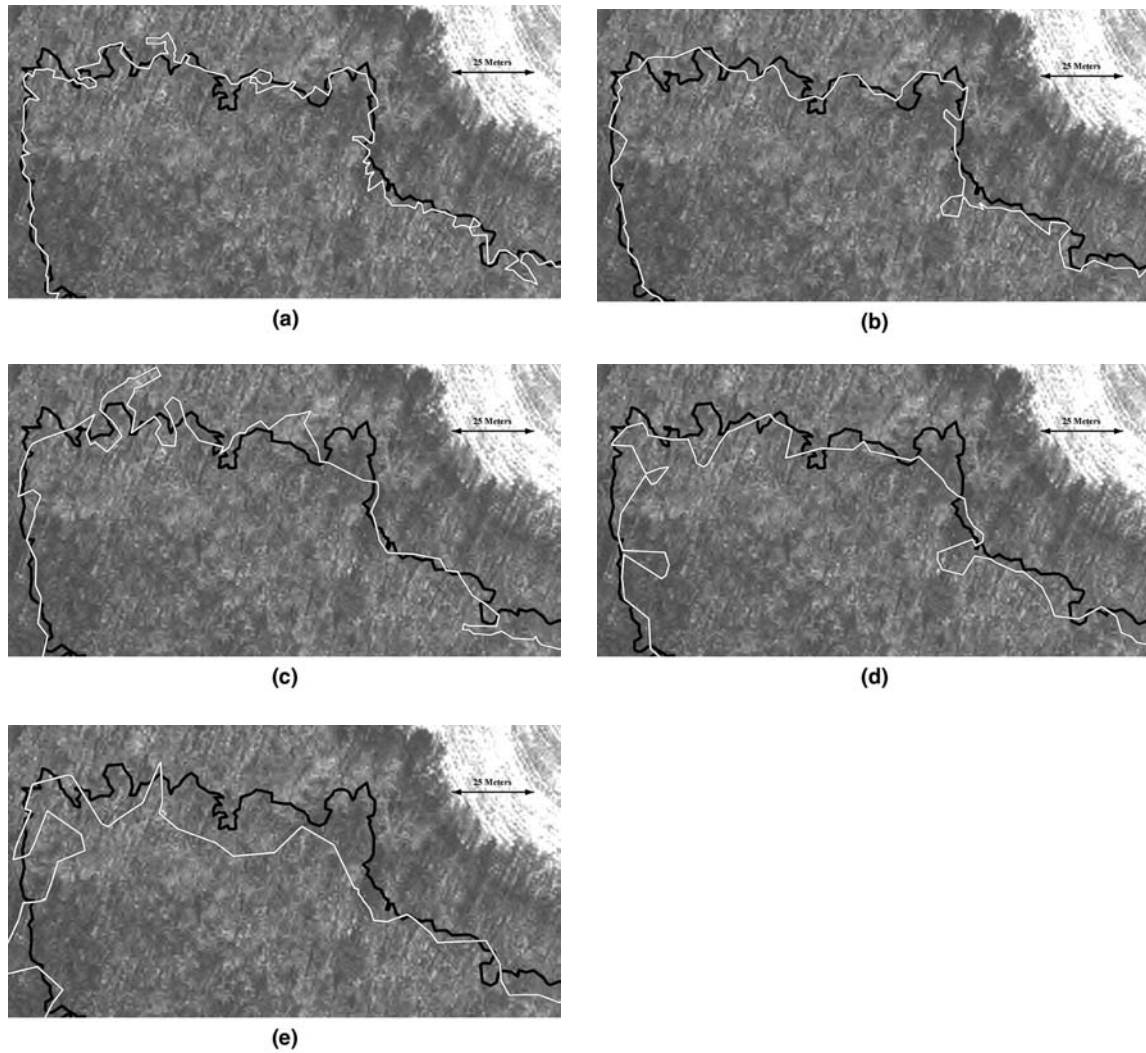


Figure 6. A detailed map of a small portion of the study area showing each of the flood zones created using  $D_0$  (the reference line shown in black in each map) and  $D_{1-5}$  (in white displayed separately in (a) through (e), respectively). The slope in this small area varies only slightly from about 1 to 3 degrees. The stream is not visible in the image but is just off the southern (bottom) end.

TABLE 3. RMSE AND MEAN ABSOLUTE ERROR BY LAND-COVER CLASS. ALL UNITS ARE METERS

Land-cover Class		Decimation Level ( $i$ )					
		0	1	2	3	4	5
Pavement $n = 41$	<i>RMSE (m)</i>	0.14	0.13	0.13	0.14	0.16	0.16
	<i>MAE (m)</i>	0.12	0.11	0.11	0.13	0.14	0.14
Grass $N = 33$	<i>RMSE (m)</i>	0.14	0.14	0.14	0.16	0.16	0.18
	<i>MAE (m)</i>	0.11	0.12	0.11	0.12	0.12	0.13
Shrub/Scrub $N = 60$	<i>RMSE (m)</i>	0.37	0.38	0.45	0.35	0.39	0.33
	<i>MAE (m)</i>	0.26	0.28	0.32	0.25	0.28	0.26
Mixed $n = 37$	<i>RMSE (m)</i>	0.26	0.35	0.37	0.35	0.37	0.36
	<i>MAE (m)</i>	0.20	0.23	0.28	0.28	0.32	0.28
Deciduous $n = 83$	<i>RMSE (m)</i>	0.39	0.43	0.41	0.42	0.42	0.43
	<i>MAE (m)</i>	0.27	0.29	0.29	0.30	0.31	0.32
All Points $n = 242$	<i>RMSE (m)</i>	0.31	0.34	0.36	0.33	0.35	0.34
	<i>MAE (m)</i>	0.21	0.23	0.24	0.24	0.25	0.25

In each of these tests, the resulting test statistic was significant (not shown), thus rejecting the null hypothesis.

*Error Related to Post spacing*

For *Hypothesis 1*, we tested the following null hypothesis using a repeated measures ANOVA test:

$$Elevation Error_0 = Elevation Error_1 = \dots = Elevation Error_5$$

where *Elevation Error* above is calculated as mean absolute error.

A repeated measures ANOVA test is analogous to paired sample *t*-test but is useful when more than two measurements are taken for each observation (survey point location). In this application we have six different measurements. The repeated measures ANOVA also allowed for the testing of interaction using the class variable. We tested the interaction of land-cover class with elevation error to determine if the nature of this relationship was significantly affected by land-cover. Table 4 below reports the results of the repeated measures test.

Based on these results, the null hypothesis stated above is rejected at the 0.05 level. Significant error differences exist through the decimation ranges examined. A pair-wise comparison of decimated datasets was performed. Tabular results of this analysis are depicted in Table 5. Note that  $D_0$  is the only decimation level that is statistically significant from any other level ( $D_2$ ,  $D_4$  and  $D_5$ ).  $D_3$  is not statistically different from any level.

*Error Related to Post spacing by Land-cover*

The interaction in the above test was insignificant indicating that the nature of the relationship is not significantly different across land-cover categories. Indeed, when we preformed another ANOVA test using only the *grass* and *pavement* categories, there was no significant difference in the error. Thus, although an error trend is apparent in these two classes, after inspection it is not significant.

To further explore the differences in error trends, we preformed a repeated measures ANOVA on each of the land-cover classes individually. Five different tests were performed (one for each land-cover class) using the following form:

For Grass:  $Elevation Error_0 = Elevation Error_1$

$$= \dots = Elevation Error_5$$

For Pavement:  $Elevation Error_0 = Elevation Error_1$

$$= \dots = Elevation Error_5$$

...

For Mixed:  $Elevation Error_0 = Elevation Error_1$

$$= \dots = Elevation Error_5.$$

Only the test in the *mixed* category was significant (Table 6). However, inspection of Table 4 (discussed above) indicates that through the ranges tested there is no patten of increasing error with increased post-spacing. Interestingly, the *pavement* class approached significance at the 0.05 level, and also exhibits an observable monotonic trend through the post-spacing values tested.

A pair-wise comparison of the two classes in which a pattern is visually apparent (*pavement* and *grass*) was also examined. There were no significant differences in any paired set for the *grass* class. However, there were a number of significantly different pairs in the *pavement* category. Those results are reported in Table 7. Another interesting result is that  $D_4$  was significantly different that the datasets with a smaller post-spacing. In summary, the only class to exhibit an observable monotonic trend *and* significant differences the relationship between post-spacing and DEM accuracy was the pavement class. This indicates that perhaps the presence of vegetation, slope, or another interacting variable introduces enough noise to mask the effects of changing the post-spacing variable, at least through the values tested.

**Hydraulic Sensitivity and Post-spacing**

Ground reference information for the 100-year flood stage and extent is often not readily available. Therefore, this portion of the research is as a sensitivity study, rather than an accuracy assessment. A sensitivity study for this application answers the question "How might one expect an answer to differ if lidar data is collected at nominal post-spacing *i* rather than the lower post-spacing (2 meters)." Each variable examined (flood elevation and flood zone extent) is compared to and thus normalized by the variable produced

TABLE 4. RESULTS OF THE REPEATED MEASURES ANOVA TEST TO DETERMINE IF DIFFERENCES IN ERROR EXIST RELATED TO POST-SPACING

Source	Sum of Squares	Df	Mean Square	F	Significance
Post-spacing (Decimation Level)	.256	5	0.051	2.643	<b>.022</b>
Post-spacing* Land-cover	.444	20	0.022	1.145	.295

TABLE 5. A PAIR-WISE COMPARISON OF THE MEAN ABSOLUTE DIFFERENCES IN ERROR BETWEEN POST-SPACING DATASETS. SIGNIFICANT DIFFERENCES ARE SHOWN IN **BOLD ITALIC**. ALL UNITS ARE METERS AND ARE NOT SIGNIFICANCE VALUES

	$D_0$	$D_1$	$D_2$	$D_3$	$D_4$	$D_5$
$D_1$	.015					
$D_2$	<b>.030</b>	.016				
$D_3$	.025	.010	.005			
$D_4$	<b>.041</b>	.027	.011	.016		
$D_5$	<b>.035</b>	.020	.005	.010	.006	

TABLE 6. THE SIGNIFICANCE LEVELS FOR THE REPEATED MEASURES TESTS DONE BY LAND-COVER (EXPLAINED ABOVE)

Land-cover	Significance
Pavement	.061
Grass	.687
Scrub/Shrub	.194
Mixed	<b>.024</b>
Deciduous	.343

TABLE 7. A PAIR-WISE COMPARISON OF THE MEAN ABSOLUTE DIFFERENCES IN ERROR BETWEEN POST-SPACING DATASETS FOR JUST THE PAVEMENT CLASS. SIGNIFICANT DIFFERENCES ARE SHOWN IN **BOLD ITALIC**. ALL UNITS ARE METERS AND ARE NOT SIGNIFICANCE VALUES

	$D_0$	$D_1$	$D_2$	$D_3$	$D_4$	$D_5$
$D_1$	.008					
$D_2$	.004	.004				
$D_3$	.009	.017	.014			
$D_4$	<b>.020</b>	<b>.028</b>	<b>.024</b>	.011		
$D_5$	.025	<b>.033</b>	.030	.016	.005	



using the lowest post-spacing ( $D_0$ ) terrain information. As discussed previously, the  $D_0$  dataset did exhibit the lowest overall error.

#### Analysis of the Flood Elevation Sensitivity

Table 8 reports the mean absolute differences between each set of water surface elevations ( $WSE_i$ ) and  $WSE_0$ . The RMSE value is also reported. Again, no strong monotonic pattern can be seen as post-spacing increased. It is also interesting to note that in each case, the mean absolute error was very close to 0.1 feet (both metric and standard units are reported), which is a typical reported accuracy for *detailed* flood studies. Often when floodwater surface elevations are reported in limited detail studies, they are rounded to the nearest 0.5 foot, well above any of the difference seen in the table.

Similar to the hypothesis tested above, we conducted a repeated measures ANOVA test to assess whether or not there was a significant difference in the water surface elevation ( $WSE$ ) change. The water surface values at each cross-section were used as the observations. This time there were only five factors examined since the  $D_0$  dataset was used as the reference and the null hypothesis took the following form:

$$\begin{aligned} |WSE_1 - WSE_0| &= |WSE_2 - WSE_0| = |WSE_3 - WSE_0| \\ &= |WSE_4 - WSE_0| = |WSE_5 - WSE_0|. \end{aligned}$$

No interaction effects were tested with this hypothesis. Table 8 also reports the results of the repeated measures test. Based on these results, the null hypothesis stated above cannot be rejected. Therefore, it must be concluded that regarding floodwater surface elevation, no significant sensitivity to post-spacing exist through the ranges examined. Given the weak significance that was exhibited in the vertical accuracy of the datasets, it was not surprising that no significant differences were found in water surface elevations.

#### Analysis of the Flood Zone Sensitivity

There are a number of methods that have been developed to quantify uncertainty in linear features. One set of related techniques is often referred to as the *buffer overlay statistic* (BOS) (Tveite and Langaas, 1999). These methods operate by buffering either one or both sets of two representations of the same line features and then comparing the buffers. Goodchild and Hunter (1997) used the single buffer approach to examine the agreement of two lines, one of which was assumed to be more accurate than the other. Their technique recursively varied the buffer distance ( $x$ ). At each value for  $x$  the proportion of the test line that was within the buffer was calculated, thus enabling a discrete solution for the function  $p(x)$  to be derived:

$$p(x)=y \tag{2}$$

where  $y$  is the desired level of desired positional accuracy (e.g., 0.95).

TABLE 8. THE RESULTS OF THE FLOOD WATER SURFACE ELEVATION (WSE) SENSITIVITY ANALYSIS. THE SIGNIFICANCE LEVEL FOR THE REPEATED MEASURES ANOVA TEST (DISCUSSED BELOW) IS ALSO REPORTED)

		Decimation Level ( $i$ )					Sig.
		1	2	3	4	5	
$WSE_i - WSE_0$	RMSE	0.16	0.20	0.20	0.20	0.19	0.68
	MAE	0.11	0.13	0.14	0.15	0.13	
Feet	RMSE	0.048	0.060	0.062	0.060	0.059	
	MAE	0.033	0.039	0.044	0.046	0.040	

Other researchers including Hodgson and Cheng (2004) and Tveite and Langaas (1999) utilized two buffers to quantify the differences in two sets of lines. Hodgson and Cheng (2004) point out that this method simultaneously accounts for both errors of commission and omission, and thus becomes a measure of the agreement between two sets of features. The statistic for the two buffer approach involves a polygon overlay operation for the two sets of buffers similar to the one buffer approach. The statistic ranges from 0 to 1, where 1 represents complete agreement.

In order to quantify the sensitivity of flood zone boundary location with respect to the post-spacing, we utilized three linear feature agreement statistics in this research. First, the single Buffer Overlay Statistic (BOS), second, a variation of the two-buffer statistic as a measure of feature agreement and finally, a statistic for the quantification of the average error per unit length of flood zone boundary.

We examined the flood zone sensitivity using variations of the GIS-based Buffer Overlay Statistic (BOS) method described above. The flood zones ( $FZ_i$ ) derived from the decimated datasets ( $D_i$ ) were examined in relation to their sensitivity across decimation levels. First, the single buffer overlay method was used to examine at what distance more than 95 percent of the flood zone boundary of  $FZ_i$  existed within the buffer of  $FZ_0$ . In terms of Equation 2, this is the value of  $x$  where:

$$p(x)_i = 0.95. \tag{3}$$

We designed a simple iterative programming routine to find the value for  $x$  at each step. We then interpolated the solution for  $x$  in Equation 3 based on this output. It is interesting to note the apparent pattern in the increase of the value for  $x$  through the range of post-spacing values.

The value of  $x$  at  $y = 0.95$  was also derived for two land-cover classes and three slope classes. This was done through simple GIS clip operation with a series of polygon GIS layers representing these classes. The land-cover classification involved classifying the CIR orthophoto into regions of forested and non-forested polygons. A simple reclassification operation was performed to derive slope polygons based a slope grid extracted from the lidar data, but at a 30 m resolution. We did this to mask the effects of very large local slopes that produced very noisy results. Table 9 reports the discretely approximated values for  $x$  found through iterative solution processing.

These classes are not mutually exclusive. However, the sets of land-cover class and slope classes are mutually exclusive and exhaustive. Note that in all cases, except the low slope class, a monotonic function with post-spacing is observed. Using this information, one could map the uncertainty in flood zone boundary location as a variable width epsilon band. Further research would be needed to validate the predictive nature of this relationship.

TABLE 9. THE APPROXIMATED VALUES FOR  $x$  (BUFFER SIZE) AT  $p(x) = 0.95$ . THEY CAN BE INTERPRETED AS 95 PERCENT OF  $FZ_i$  IS WITHIN  $x$  OF  $FZ_0$ . VALUES ARE REPORTED IN METERS

		Decimation Level ( $i$ )				
Classification		1	2	3	4	5
Land-cover	Forested	4.13	6.13	5.88	6.38	8.38
	Open	2.63	3.63	3.63	4.63	5.13
Slope	Low 0–3°	10.38	14.88	9.63	8.88	13.88
	Med 3–10°	2.88	4.13	4.63	5.13	6.63
	High 10–90°	1.63	3.13	4.13	4.63	6.13
Overall		3.88	5.63	5.63	6.13	7.88

TABLE 10. THE RESULTS OF THE FEATURE AGREEMENT CALCULATIONS. AS IN THE VARIATION OF  $p(x) = 0.95$ , THE FEATURE AGREEMENT INCREASES AT A STEADY RATE THROUGH THE RANGE OF POST-SPACINGS

Category	Decimation Level ( <i>i</i> )				
	1	2	3	4	5
$FZ_i \cap FZ_0$ (Overlapping area m <sup>2</sup> )	1538012	1530600	1527066	1523420	1521917
$FZ_i \cup FZ_0$ (Total Area m <sup>2</sup> )	1550394	1548670	1546653	1543077	1546712
$FA_i$	86.67	80.20	77.94	76.34	73.78
Commission					
Area m <sup>2</sup>	133277	194501	210828	211577	266891
%	0.800	1.168	1.266	1.270	1.602
Omission					
Area m <sup>2</sup>	103638	183424	221457	260702	276889
%	0.621	1.100	1.330	1.570	1.663

The two buffer BOS method set forth by Hodgson and Cheng (2004) was modified for use with polygon features, rather than line features. Since the features being dealt with are already polygons, no buffering was needed. The overall goal is to provide a measure of feature agreement that accounts for both the differences of commission ( $FZ_i$  exist where  $FZ_0$  does not) and errors of omission ( $FZ_i$  does not exist where  $FZ_0$  does). This feature agreement statistic ( $FA$ ) was calculated by dividing the area of intersection of both flood zones by the intersection plus the symmetric difference or XOR of the same pair in the following manner:

$$FA_i = \frac{FZ_i \cap FZ_0}{FZ_i \cap FZ_0 + FZ_i \setminus FZ_0} * 100. \quad (4)$$

Table 10 reports the results of these last two analyses. It is apparent that through the range of post-spacing, the feature agreement decreases rather steadily as the value for  $p(x) = 0.95$  did above. An interesting finding is that the dominance of commission error over omission error appears to reverse itself at  $D_3$ . Another interesting phenomenon is that the total area of the flood zone decreases through each post-spacing  $FZ_1$  to  $FZ_4$  but then increases at  $FZ_5$ .

The feature agreement statistic, while ideal for comparing relative agreement of flood zones along the same stream, would not be appropriate for comparing two different streams. For example, in the case of two streams with equal length bank distance and boundary uncertainty, but each having different total areas due to increased width, the stream with a narrower channel would have lower values for feature agreement than a larger one just because it shares more area in common under the flood zone.

A final analysis of flood zone sensitivity attempts to quantify the average flood zone boundary difference (FBD) per unit length of boundary. We calculated this statistic as:

$$FBD_i = \frac{FZ_i \setminus FZ_0}{FBL_0} \quad (5)$$

where  $FBL$  = Flood Zone Boundary Length.

Since the numerator is area of the symmetric difference between the two polygons (measured in units<sup>2</sup>) and the denominator is the length of the reference flood zone boundary, the statistic is in length units. This statistic allows for the input parameters to be broken out by class similar to the single buffer approach above. The results of the FBD statistic are provided in Table 11. The statistic was calculated for the entire study area and then broken down by omission and commission. Additionally, the statistic was calculated by land-cover and then by slope class.

TABLE 11. THE FBD STATISTIC DESCRIBED ABOVE IS CALCULATED ON THE ENTIRE AREA AND IS BROKEN OUT BY THE SAME CLASSES AS IN THE VERTICAL ERROR ANALYSIS ABOVE. VALUES ARE REPORTED IN METERS

Classification		Decimation Level ( <i>i</i> )				
		1	2	3	4	5
$FBD_i$		0.85	1.35	1.55	1.69	1.95
Commission	$FBD_i$	0.48	0.70	0.75	0.76	0.95
Omission	$FBD_i$	0.37	0.66	0.79	0.93	0.99
Land-cover	Forested	0.88	1.40	1.58	1.71	1.97
	Open	0.68	1.06	1.33	1.54	1.78
Slope	Low 0–3°	1.39	2.11	2.16	2.31	2.52
	Med 3–10°	0.74	1.19	1.40	1.54	1.75
	High 10–90°	0.49	0.88	1.20	1.34	1.78

Not surprisingly, the patterns exhibited in this analysis were similar to the single BOS. This is because each statistic examined similar variables. The major difference between the BOS and FBD in terms of trend is that *all* of the FBD classes form an increasing monotonic function through the range of tested post-spacing values. With the BOS statistic, the low slope class, and to a much smaller degree the forested class both had dips and valleys progressing through the post-spacing range.

## Discussion

The most intriguing finding of this research was the absence of the discovery of a significant pattern relating error in DEM accuracy to post-spacing through the range of post-spacing values tested. Previous research has established that such a relationship should exist. Therefore, it is likely that a pattern relating error to sampling intensity does exist. The absence of such a pattern in this empirical data is likely caused by the fact that this relationship, when examined at this fine a scale is not apparent through the noise inherent in the data, the data collection process, or the fine detail of the terrain itself. This logic is further supported by examining the general trend that is apparent, though insignificant, in both the *pavement* and *grass* classes. This is an important finding since it implies that more lidar data is not *always* beneficial in the flood mapping application, especially when cost is considered. Further, these findings suggest that there may be certain cases where having more data is not only redundant, but may increase error in the final product. This appears as though it may be the case in the *scrub/shrub* class above in which the DEM created from the highest post-spacing interval is the most accurate for this class.

The base flood elevation sensitivity exhibited no significant differences or visible patterns across the post-spacing variable. This is not surprising considering that little differences or patterns were found in the DEM when considered against the same variable of post-spacing.

The position of the flood zone boundary was sensitive to the variable of post-spacing. Whether this is a practically significant finding is a topic of debate for land owners, policy makers, and insurance companies. A relationship apparent in this variable and not the others likely because flood zone boundary is more a function of surface form accuracy than absolute vertical accuracy, and surface form accuracy varies at a higher rate that is not as easily masked by the data or terrain noise. Further empirical research using variable post-spacing lidar data would be useful. It would require extensive ground reference information on a 3D surface form.

Although the portability of these empirical relationships is limited, the research is important for a number of reasons. First, the study area is not unique in terms of its terrain, physiography, and other environmental variables especially in flood prone areas. The piedmont/upper coastal plane stretches across the entire southeastern United States and often experiences severe tropical weather systems. In fact, flooding generated by such an event was one of the original impetuses for the research. Second, this research establishes a methodology for conducting similar studies in other areas. This includes both the data collection and processing procedures. Finally, it demonstrates that achieving a lower post-spacing is not efficient or desirable for every application.

Taken as whole, the results of the study make it difficult to justify acquiring lidar data at less than about 4 m post-spacing (the equivalent of  $D_2$  or  $D_3$ ) for this application under similar conditions. It was at this point that any observable trend was apparent in the accuracy of the lidar-derived DEM surface. The results also indicate that improvement to the lidar collection and processing that would tighten the error distribution would be needed in order to truly benefit from collecting datasets with post-spacing below this threshold. Further research should be performed to examine the trend over larger post-spacing values, and in other types of terrain conditions. It should be noted that there are other applications, such as mapping forestry parameters that depend on higher resolution lidar data. When acquiring lidar data that will ultimately be cross-utilized, each potential utilization should be considered when evaluating post-spacing requirements.

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## References

- Ackerman, F., and K. Kraus, 2004. Reader commentary: Grid based digital terrain models, *GeoInformatics*, 6(7):28–31.
- Bolstad, P.V., and T. Stowe, 1994. An evaluation of DEM accuracy: Elevation, slope and aspect, *Photogrammetric Engineering & Remote Sensing*, 60(11):1327–1332.
- Clark, W.A.V., and K.L. Avery, 1976. The effects of data aggregation in statistical analysis, *Geographical Analysis*, 8:428–438.
- Cobby, D.M., D.C. Mason, and I.J. Davenport, 2001. Image processing of airborne laser altimetry data for improved river modeling, *ISPRS Journal of Photogrammetry and Remote Sensing*, 56(2): 121–138.
- Cowen, D.J., J.R. Jensen, C. Hendrix, M.E. Hodgson, and S.R. Schill, 2000. A GIS-assisted construction model that incorporates lidar data, *Photogrammetric Engineering & Remote Sensing*, 66(11): 1323–1326.
- FEMA, 2002. Map Modernization Objective: Automated Hydrology and Hydraulics (H&H) Floodplain Mapping, URL: [http://www.fema.gov/mit/tsd/mm\\_ahh6.htm](http://www.fema.gov/mit/tsd/mm_ahh6.htm) (last date accessed: 19 March 2007).
- FEMA, 2003. Guidelines and Specifications for Flood Hazard Mapping Partners, Appendix A: Guidelines for Aerial Mapping and Surveying, URL: [http://www.fema.gov/pdf/fhm/fm\\_gsaa.pdf](http://www.fema.gov/pdf/fhm/fm_gsaa.pdf) (last date accessed: 19 March 2007).
- Fotheringham, A.S., and D.W.S. Wong, 1991. The modifiable areal unit problem in multivariate statistical analysis, *Environment and Planning A*, 23:1025–1044.
- Goodchild, M.F., and G. J. Hunter, 1997. A simple positional accuracy measure for linear features, *International Journal of Geographical Information Science*, 11(3):299–306.
- Hodgson, M.E., X. Li, and Y. Cheng, 2004. A parameterization model for transportation feature extraction, *Photogrammetric Engineering & Remote Sensing*, (12):1399–1404.
- Hodgson, M.E., J.R. Jensen, L. Schmidt, S. Schill, and B. Davis, 2003. An evaluation of lidar- and IFSAR-derived digital elevation models in leaf-on conditions with USGS Level 1 and Level 2 DEMs, *Remote Sensing of Environment*, 84(2):295–308.
- Hodgson, M.E., and P. Bresnahan, 2004. Accuracy of airborne lidar-derived elevation: Empirical assessment and error budget, *Photogrammetric Engineering & Remote Sensing*, 70(3):331–33.
- Hodgson, M.E., J.R. Jensen, G.T. Raber, J.A. Tullis, B. Davis, K. Schuckman, and G. Thompson, 2005. An evaluation of lidar-derived elevation and terrain slope in leaf-off conditions, *Photogrammetric Engineering & Remote Sensing*, 71(12): 817–823.
- Jensen, J.R., 2000. *Remote Sensing of the Environment: An Earth Resource Perspective*, Upper Saddle River, New Jersey, Prentice-Hall, Inc., 544 p.
- Kenward, T., D.P. Lettenmaier, E.F. Wood and E. Fielding, 2000. Effects of digital elevation model accuracy on hydrologic predictions, *Remote Sensing of Environment*, 74:432–444.
- Levin, S.A., 1992. The problem of pattern and scale in ecology, *Ecology*, 73(6):1943–1967.
- MacEachren, A.M., and J.V. Davidson, 1987. Sampling and isometric mapping of continuous geographic surfaces, *The American Cartographer*, 14(4):299–320.
- Mandelbrot, B., 1967. How Long is the Coast of Britain?, *Science*, 156:636–638.
- Manson, S.M., S.J. Ratick, and A.R. Solow, 2002. Decision making and uncertainty: Bayesian analysis of potential flood heights, *Geographical Analysis*, 34(2):112–129.
- Marks, K., and P. Bates, 2000. Integration of high-resolution topographic data with floodplain flow models, *Hydrological Processes*, 14:2109–2122.
- Maune, D.F. (editor), 2001. *Digital Elevation Model Technologies and Applications: The DEM Users Manual*, The American Society for Photogrammetry and Remote Sensing, Bethesda, Maryland, 539 p.
- Maune, D.F., 2003. FEMA's mapping and guidelines and specifications, *Proceedings of the ASPRS 2003 Fall Conference, Terrain Data: Applications and Visualization – Making the Connection*, 28–30 October, Charleston, South Carolina, unpaginated CD-ROM.
- NCFPM (North Carolina Floodplain Mapping Program), 2002. URL: <http://www.ncfloodmaps.com/> (last date accessed: 19 March 2007).
- NCFPM (North Carolina Floodplain Mapping Program), 2003. Issue 37: Quality Control of Light Detection and Ranging Elevation Data in North Carolina for Phase II of the North Carolina Floodplain Mapping Program, URL: [www.ncfloodmaps.com/pubrocs/issuepapers.htm](http://www.ncfloodmaps.com/pubrocs/issuepapers.htm) (last date accessed: 19 March 2007).

- Omer, C.R., E.J. Nelson, and A.K. Zundel, 2003. Impact of varied data resolution on hydraulic modeling and floodplain delineation, *Journal of the American Water Resources Association*, 39(2):467–475.
- Quattrochi, D.A., and M.F. Goodchild, 1997. *Scale in Remote Sensing and GIS*, CRC Press, Boca Raton, Florida, 432 p.
- Pope, B.F., G.D. Tasker, and J.C. Robins, 2001. *Estimating the Magnitude and Frequency of Floods in Rural Basins of North Carolina-Revised*, Water Resources Investigations Report 01-4207, U.S. Geological Survey, 44 p.
- Raber, G.T., J.R. Jensen, S.R. Schill, and K. Schuckman, 2002. Creation of digital terrain models using an adaptive lidar vegetation point removal process, *Photogrammetric Engineering & Remote Sensing*, 68(12):1307–1315.
- Tullis, J.A., 2003. *Data Mining to Identify Optimal Spatial Aggregation Scales and Input Features: Digital Image Classification with Topographic LIDAR and LIDAR Intensity Returns*, Ph.D. dissertation, University of South Carolina-Columbia, 100 p.
- Tveite, H., and S. Langaas, 1999. An accuracy assessment method for geographical line data sets based on buffering, *International Journal of Geographical Information Science*, 13(1):27–47.
- USACE (United States Army Corps of Engineers), 2001. *HEC-River Analysis System Hydraulic Reference Manual, Version 3.0*, Manual CPD-69, Hydraulic Engineering Center (HEC), Davis, California.

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