THE EFFECT OF LIDAR POSTING DENSITY ON DEM ACCURACY AND FLOOD EXTENT DELINEATION

A GIS-SIMULATION APPROACH

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ABSTRACT

Recently a number of local communities and a few statewide agencies have undertaken efforts to acquire more accurate digital elevation surfaces for various applications including flood hazard mapping. The technology most widely adopted for this purpose has been LIDAR remote sensing. The acquisition of a spatially dense set of elevation postings representing the "bare" ground may be the greatest factor in deriving an accurate elevation surface. Creating such a dense elevation dataset using LIDAR remote sensing requires two elements – a high raw posting density during the collection phase and rigorous post-processing to identify the "ground" returns. A higher posting density generally requires significantly higher cost associated with the LIDAR sensor and the addition technical personnel time and computing resources (processor speed, RAM, storage space, etc.) that are required to process higher posting densities to produce digital elevation models (DEMs) of the bare ground. The goal of this research is to develop a relationship between LIDAR posting density and DEM accuracy. Specifications for data collection/processing in future mapping efforts could use this empirical relationship to match target accuracy requirements with data collection/processing parameters. For this research, a simple GIS simulation was developed in order to create a LIDAR data collection over two GIS generated surfaces. The vertical and surface form accuracy of the resulting DEMs are compared to the posting density in order to establish the relationship between these variables. The research further investigates the sensitivity of horizontal accuracy (for flood extent delineation) using the generated DEMs. The results indicate that these relationships exist and validate the need for an empirical study to explore the patterns further.

INTRODUCTION

Airborne Light Detection and Ranging (LIDAR) remote sensing has become a standard method for the acquisition of topographic data. Often LIDAR data is processed to create digital elevation models (DEMs). In turn, DEMs are utilized in a variety of applications including automated hydraulic modeling for flood hazard mapping.

As one of the inputs to flood hazard mapping, the accuracy of the DEM surface has an effect the extent of the modeled flood. Acquiring a spatially dense set of elevation postings representing the “bare” ground may be the greatest determinant of obtaining an accurate DEM surface. Creating a dense elevation dataset requires a high initial posting density during the data acquisition phase. A higher posting density generally requires a more sophisticated sensor system with a higher pulse rate, a lower elevation over-flight (and therefore more flight lines), a narrower scan angle, or a combination of these variables. Beyond acquisition costs, significantly more personnel time and computing resources (processor speed, RAM, storage space, etc.) are required to process higher posting densities to produce DEMs of the bare ground. The purpose of this research is to investigate the influence of LIDAR posting density on vertical DEM accuracy and further examine the relationship between vertical accuracy and flood hazard mapping by addressing the following research questions:

1) How does LIDAR posting density affect interpolated vertical accuracy?
2) Can a relationship be developed between flood boundary uncertainty and vertical error? (The real measure of flood damage is in property or other asset damage which is influenced in a large part by the aerial extent of a flood. A measure of the uncertainty of this extent is potentially of significant value.)

The relationship between posting density and accuracy is expected to be dependent on various terrain characteristics (e.g. slope, topographic variability, and land cover.) To obtain a better understanding of this relationship, and of the factors that contribute to it, a virtual LIDAR collector was created using a GIS. This GIS-based simulation approach allows for the generation of virtual LIDAR collections over various surfaces representing different topography and land cover. Due to the complex nature of LIDAR data collection, the LIDAR simulator is not expected to be a predictive model. Rather, it will provide a basis for examining the relationships between error characteristics and the mapped flood extent based on digital surfaces that resemble those derived from a LIDAR data acquisition (i.e. irregular point spacing, skewed vertical error distributions, etc.) Eventually, the findings from the GIS-simulation approach can serve as validation to support an empirical study by comparing the resulting patterns and relationships to those seen in actual LIDAR data collected at varying posting densities. If similar patterns (error distributions, flood extent differences, etc) result from the empirical study, it will serve to validate the simulation approach. If this relationship is established, estimates on the amount of uncertainty contributed by the topographic data to the modeled flood extent could be developed. The implications of this include being able to estimate the uncertainty in delineated flood extents based on the collection parameters and terrain characteristics. Specifications for data collection and processing in future mapping efforts could use this information to match target accuracy requirements with data collection/processing parameters. The GIS-simulation technique could be used as a guide for conducting future empirical research. Figure 1 depicts the general project flow research to be undertaken. This paper presents the results of the of the initial “GIS-Simulation” portion of this study.

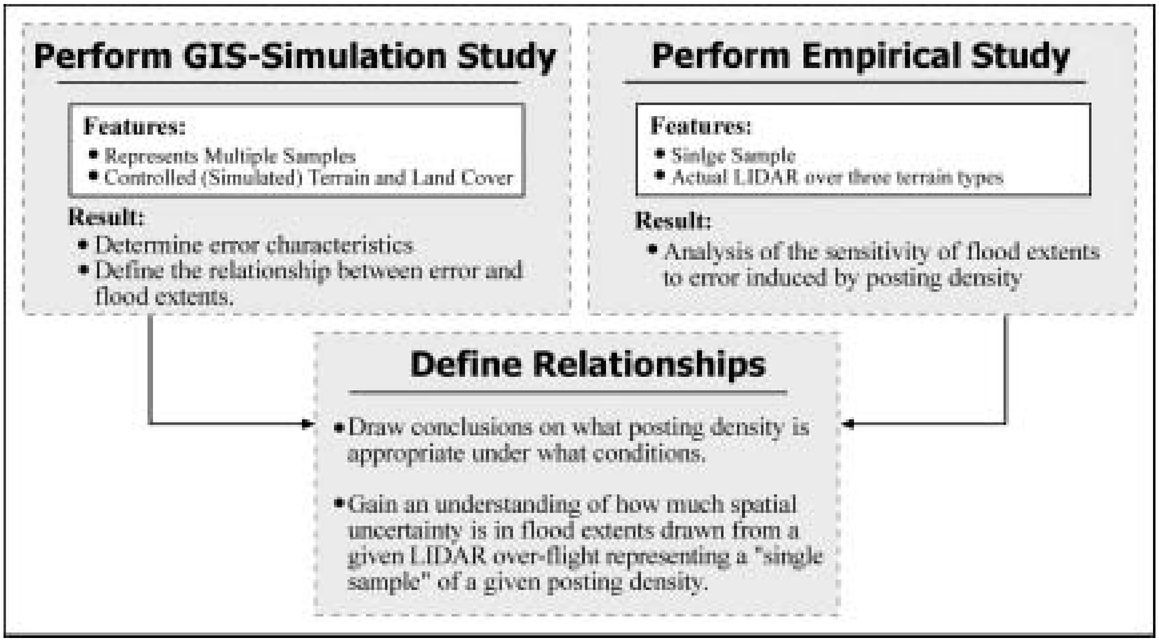


Figure 1 – A generalized flow diagram of the research.

BACKGROUND

The National Flood Insurance Program (NFIP) was established by Congress in the National Flood Insurance Act on August 1, 1968. The intent of the NFIP was to reduce future flood damage through community floodplain management ordinances, and provide protection for property owners against potential losses through an insurance mechanism that requires a premium to be paid for protection from loss. The Federal Emergency Management Agency (FEMA) is the government agency charged with overseeing the NFIP and therefore managing the risk associated with flooding. As part of this program, FEMA maintains and updates flood insurance rate maps (FIRMs). These maps delineate Special Flood Hazard Areas (SFHA). An SFHA is an area of land that would be inundated by a flood that has a 1% chance of occurrence in any given year.

In 1997, FEMA identified a need to update their database of approximately 100,000 FIRMs and initiated the Map Modernization program. At the time about half of all the FIRMs were > 10 years old. FIRMs become outdated for a number of reasons, including:

1) Land use change affects the amount of rain that will contribute to run-off and therefore flood stage during a storm event.
2) Changes to flood controls such as dams and weirs will also change the flood stage for a given storm event.
3) Technological advances or improvement to the models themselves and in the acquisition of topographic data (e.g. LIDAR, IFSAR) can also cause effective changes.

In addition to the outdated FIRMs, another 13,700 new FIRMs were needed for areas without any previous flood studies.

In creating and updating their map inventory, FEMA decided to change the way the maps were stored, accessed and updated. The older maps were created using traditional techniques that involved drawing the SFHA by hand once the flood elevations were established, and then storing the information on paper. With technological advances having been made, particularly in the areas of GIS and automated hydraulic modeling, FEMA decided to begin creation of *Digital* Flood insurance rate maps or DFRIMs. The advantages of the new digital format include:

1) The ability to efficiently integrate the spatial information used as input to the current automated water modeling techniques.
2) The ability to store the information and metadata on digital media, making maintenance and update more efficient.
3) The ability to distribute flood hazard information on digital media, including the Internet, making the information more available to policy makers and the general public.

Part of the FEMAs Map Modernization undertaking has involved creating formal partnerships with flood prone communities in order to update and create the DFIRMs for there areas. Communities that enter into this partnership are designated Cooperative Technical Communities (CTCs) and agree to contribute to the engineering and mapping effort.

Due to a number of contributing factors including the flood damage sustained during the 2000 hurricane season, the State of North Carolina has undertaken a massive project to update the flood insurance rate maps (FIRMs) for the entire state. This initiative, called the North Carolina Floodplain Mapping program, is supported by State funds, as well as FEMA as part of their Map Modernization Program. In fact, the state of North Carolina was designated as the first Cooperative Technical State (CTS) by FEMA in this effort. This means that North Carolina has full responsibility for the creation of the next generation of FIRMs now referred to as, *Digital* Flood Insurance Rate Maps (DFIRMs), within its state boundaries (North Carolina, 2002). In the future, other states will follow North Carolina in undertaking the same effort for there states. In fact, South Carolina is recently accepted a bid on for a statewide topographic data (LIDAR) acquisition primary for the modernization of the flood maps.

LIDAR has been used as the primary method for acquiring the topographic data required for the North Carolina effort. Outside of claims made by the LIDAR vendors themselves, little is known about the accuracy of LIDAR under various conditions and collection parameters. A handful of empirical studies have been performed to asses the accuracy of LIDAR derived DEM products collected in various conditions (Hodgson et al 2003, Raber et al. 2002). Although significant research exists on how sampling intensity or resolution affects vertical accuracy, very little empirical research has tested the effect of LIDAR posting density on vertical accuracy. Since posting density is the one of the greatest cost factors to LIDAR data acquisition, research in this area has the potential to provide policy direction regarding funding limitations and accuracy requirements. The State of North Carolina, along with other federal agencies like NASA, FEMA, and the

Army Corps of Engineers (USACE) are interested in understanding how posting density affects vertical accuracy, as well what affects posting density would have on the hydraulic analysis (North Carolina 2002).

There are two primary ways in which the accuracy of the topographic data can have an effect on the delineation of a flood zone on a FEMA flood map. The USACE developed the error model shown in Figure 2. Topographic uncertainty first contributes to uncertainty in the discharge-stage relationship when used in the modeling of the hydraulic process in order to derive discharge (Q) and stage (H), or flood elevation.

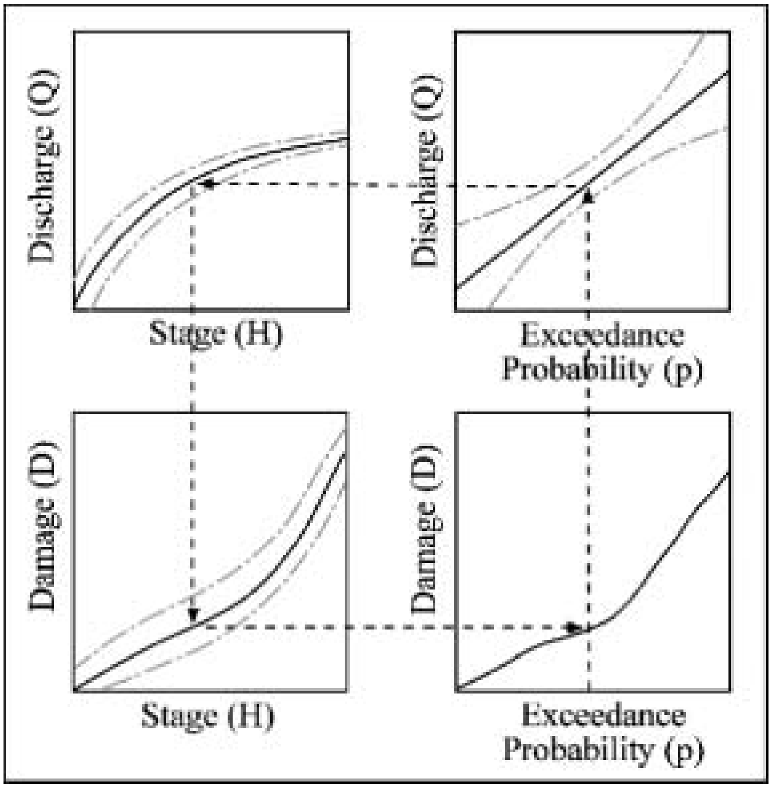


Figure 2 – A model of the relationships that influence the uncertainty in flood risk assessment (adapted from NRC, 2000.)

Since FEMA uses the 100 year flood event as the basis for establishing the SFHAs, FEMA refers to the flood elevations derived for the 100 year flood as *base flood elevations* (BFEs).

The other way in which topographic uncertainty contributes to the uncertainty is in the stage-damage relationship when it is used to delineate the flood extent or flood zone (i.e. the boundary of the SFHA). After the BFEs are established along a river channel, the flood extent is then determined using topographic GIS data. Often, particularly in the United States, large scale hydraulic studies are preformed utilizing software that takes advantage of one-dimensional finite differencing equations between successive upstream surveyed transects, e.g. HEC-RAS (Buckley 2001). One advantage of this approach is that, the topographic data does not need to be continuous (i.e. it is only needed along transects), however, a continuous GIS layer (i.e. DEM) is needed to delineate the flood extents (USACE 2001).

The influence of the quality of the topographic transect data on the produced BFE will not be addressed in this research. However, the Corps (USACE, 1996) did a simulation based study that specifically addressed the affects of modifying this topographic input by introducing error in surveyed transects and running them through a hydraulic model. At the time HEC-RAS was not developed, instead the predecessor HEC-2 was used. In addition, the study was performed from the perspective of having USGS topographic maps, or photogrammetric measurements rather then LIDAR as an alternative to *in situ* ground surveys. They used as the basis for the study the hydraulic output generated from the topographic survey, and then simulated photogrammetric measurements or those taken from a map at the same sample locations. Error was added to the “photogrammetric” and “map” measurements based on the known accuracy of these methods. This random error was assumed to be normally distributed. They found the error (RMSE) used to generate the test transects was a good predictor of the amount of error present in the BFE calculation.

PREVIOUS RESEARCH

Two main themes relating to the stated research questions will be addressed in this research. First, “How does posting density effect vertical error?”, and second “How does this vertical error relate to flood zone delineation?” Both of these questions contain elements of very basic geographic problems. Posting density is basically a question of resolution or scale. The relationship between horizontal and vertical error is a classic topic that has been studied in context of many DEM derivatives including contour lines and viewsheds.

A body of research exists on assessing the vertical accuracy and other derivatives (slope, aspect, etc.) of various digital elevation surfaces. Much of this research has been done over the last 10-15 years 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 varying posting densities. For example, MacEachren and Davidson (1987) found that the observed error in DEM surfaces increased at an increasing rate as the cell size was increased. This effect was observed on a number of surfaces, although the general form of the relationship was constant, the curves had varying degrees of starting points and increasing rates. This effect appeared to be related to the complexity of the topographic relief exhibited by the tested surface.

It is generally understood that there are a variety of factors influencing the accuracy of LIDAR derived DEMs. A general summary of the sources of these errors can be found in Maune (2001) and in Table 1. A common way to perform an empirical assessment of observed DEM accuracy is to use the RMSE statistic based on high grade *in situ* survey spot elevations in the following manner:

$$RMSE_{observed\_DEM} = \frac{\sqrt{\sum (Z_{LIDAR} - Z_{Survey})^2}}{n} \qquad [1]$$

A number of studies have empirically assed the accuracy of DEMs under various conditions. For example, Bolstad and Stowe (1994) examined and the compared the errors exhibited by a USGS topographic DEM and a DEM derived from a Stereo SPOT image. Later work has examined error in LIDAR derived DEMs as influenced by land cover and slope (Hodgson et al. 2003a, 2003b.) Cowen et al. (2000) tested for a relationship between canopy closure and accuracy. Many of these studies also examined the effect of the various conditions on slope error. In recent work, Hodgson and Bresnahan (2003) present an error budget model for a LIDAR derived DEM surface in the following equation:

$$RMSE_{observed\_DEM} = \sqrt{RMSE^2_{LIDAR\_System} + RMSE^2_{HorizError,Slope} + RMSE^2_{Interp} + RMSE^2_{Survey}} \qquad [2]$$

where: $RMSE^2_{LIDAR\_System}$ = The contributing error from the LIDAR system
$RMSE^2_{HorizError,Slope}$ = Elevation error introduced from horizontal displacement (Equation 3)
$RMSE^2_{Interp}$ = Elevation error introduced through interpolation
$RMSE^2_{Survey}$ = Error in the survey used to calculated observed RMSE

By collecting survey elevations at exactly the same locations as LIDAR points, the authors were able to decompose the errors and observe the contributions of each of the above sources to the overall observed error. This was also done by land cover class. As in other research, the error varied by land cover type. As one of the goals of this research will be to simulate LIDAR-like error over a surface, a discussion of the current knowledge of what induces the error is important.

Table 1 – Important Concepts Related to LIDAR Surface Accuracy Variations (from Hodgson et al. 2003b)

			LIDAR POINT PROCESSING	**GEOGRAPHY**
Sensor	**Aircraft**	**Navigation**		
Pulse Length	Altitude	GPS constellation	Return Identification	Seasonality
Pulse Rate	Forward Speed	Inertial Navigation System	Automated Labeling Algorithm	Land Cover
Wavelength			Human Classification	Terrain Slope
Divergence			Interpolation Algorithm	
Scan Angle				

LIDAR System Errors

A LIDAR system measures the range (distance), a laser pulse travels. A pulse of laser energy is transmitted from the LIDAR system toward the ground. After the pulse interacts with objects on the ground, some of the energy is reflected back toward the LIDAR system and recovered by the receiver. The position of the unit is known through a combination of precise global positioning system (GPS) measurements, and the aircraft internal navigation system (INS) which accounts for the pitch and roll. Knowing the angle and the absolute position of the instrument allows for relatively precise and accurate location (x,y,z) of the laser pulse's destination. Usually all the information that is needed to collect accurate points (laser travel time, scan angle, INS measurement, etc) is stored separately in the LIDAR unit and processed later to (x,y,z) point locations.

The system error associated with the instrument's ability to report a specific location during the collection of points is generally reported to be on the order of 15 – 20 cm RMSE vertical. This is based on empirical measurements under ideal conditions. However, it is know that even under these conditions the error is not constant and often demonstrates a bias. For example scanning systems often demonstrated higher errors (i.e. wider distributions about the mean) off-NADIR then at lower scan angles (Box, 2001.) The LIDAR data acquired for Hodgson et al, (2003b) showed a tendency to under-predict error, even in pavement and low grass categories.

Another source of error introduced to derived digital elevation surfaces by the LIDAR "system" is the error introduced during the point labeling process. The point labeling process involves determining which LIDAR points reached the ground and which did not. Errors introduced during this process can produce unnecessary interpolation error (when ground points are incorrectly labeled non-ground points) and over-prediction error (when non-ground points are incorrectly labeled ground points.)

Horizontal Displacement Error

Another impact on the ability of the sensor to acquire an accurate measurement comes from the terrain itself, particularly the slope. This phenomena is based on Koppe's formula highlighted in the next section (Equation 3.) Basically, the tendency of the sensor to have errors in horizontal measurements is related to the apparent vertical errors through the slope. The size of a LIDAR footprint is usually determined by the beam divergence and the flying height. On commercial systems the footprint is often smaller then a meter when it reaches the ground. However, the vertical (z) and horizontal (x,y) position that is reported can come from anywhere within the footprint (Box 2002.) This effect was accounted for in the research done by Hodgson above as $RMSE^2_{HorizError,Slope}$.

Interpolation Error

Interpolation error is introduced whenever a surface is derived from point observations as is the case with LIDAR. Interpolation error is a result of many factors including: a) the algorithm used, b) the terrain variability (terrain that follows a predictable trend can be interpolated with less error), and c) distribution of the point observations. In the context of the proposed research, posting density is very much related to latter. There are actually two different types of LIDAR posting density:

1) *Nominal* or the initial posting density is often considered a function of height above ground, scan rate, and the forward speed of the aircraft, as well as any overlap of data from neighboring flight lines.
2) *Observed* posting density is related to the initial posting density, but is also influenced by terrain characteristics like surface form and land cover that contribute to the removal of non-ground points during the point labeling or "vegetation removal" process.

The point labeling process contains two phases the automatic phase and the manual phase. The automatic phase consists of running the points through a computer based algorithm that removes points that are less likely to be ground points based on local data trend filters. Once the automatic processing has occurred, the resulting dataset is then further refined by a human operator. Some areas in which problems remain after automatic processing include low-lying dense vegetation, extremely steep terrain, and various man-made objects (overpasses, bridges, odd shaped buildings, etc.). The operator often utilizes a number of "off-the-shelf" and custom software applications that allow him or her to view the LIDAR data points in three dimensions and / or with ancillary information (e.g. orthophoto.) The operator then interactively removes, or adds points based on their judgment of where the ground is. It is estimated that 85 – 90 % of the points are identified using the automatic algorithm, with the remainder being done using the interactive human editing process. However the manual processes is much more time consuming and costly.

As discussed previously, research has been done to asses the effects of varying resolution on DEM accuracy (MacEachren and Davidson), however little work has been done that specifically examines the relationship between LIDAR posting density and accuracy. One interesting study by Lloyd and Atkinson (2002) used a jack-knifing approach and demonstrated with LIDAR data that the error in vertical accuracy changed differently according to the interpolation algorithm used. As part of their approach, more and more LIDAR points were removed from inclusion in the surface model and included in the validation phase, thus effectively changing the posting density. Although the concept of LIDAR posting density is similar to the DEM resampling of MacEachren and Davidson discussed above, especially in the simulation approach proposed in this research, there are some significant difference to point out.

1) LIDAR posting is often discussed in at a different scale (in the range of 1 – 10m vs 30m USGS DEMs).

2) Different factors influence the vertical error of a LIDAR point. These factors are discussed in some detail below.

3) A LIDAR system basically semi-systematically samples a surface, but the land cover characteristics determine which and how many points are removed in the point labeling process. In vegetated areas the pattern of removed points is fairly random.

The relationship between vertical accuracy and flood extent, is essentially a problem of relating vertical (z) error with observed horizontal error (x,y), and slope. This is a well documented relationship often referred to as Koppe's formula (Maling, 1989):

$$V_e = H_e * \tan \alpha \qquad [3]$$

where: V_e = vertical error or offset

H_e = horizontal error or offset

α = slope of the surface

Expressed in terms of the horizontal error this becomes:

$$H_e = \frac{V_e}{\tan \alpha} \qquad [4]$$

This is demonstrated in the context of flood zone delineation in 2-D along a hypothetical transect in Figure 3a.

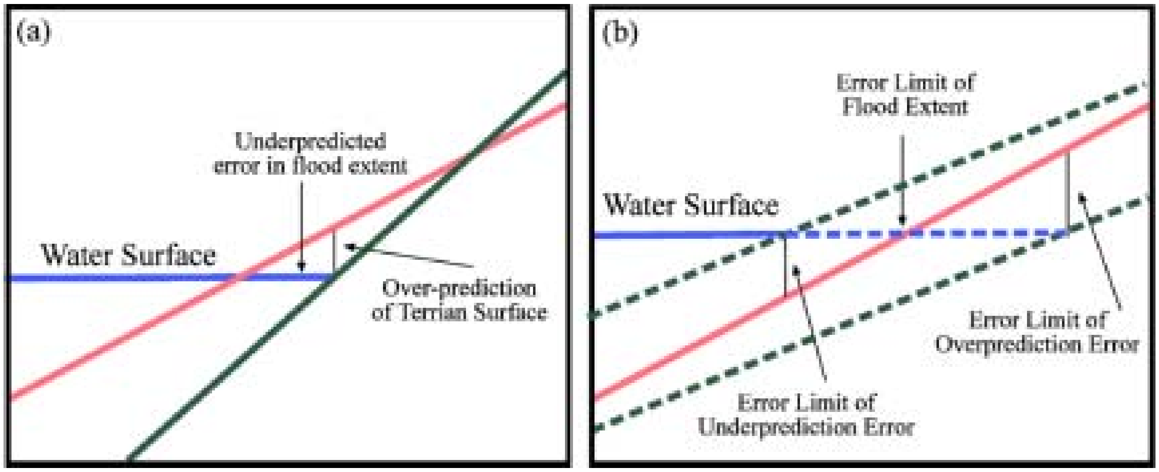


Figure 3 – The relationship of vertical error to horizontal error through the slope can be applied to flood mapping.

When local horizontal error is not precisely known, an error statistic like vertical RMSE could be used to create uncertainty estimates in the horizontal error (Figure 3b)

Or, expressed for in general for a given region the following relationship should exist.

$$Error_{Horixontal} \propto \frac{RMSE_{Vertical}}{\tan \overline{\alpha}} \qquad [5]$$

The relationship defined by the above equations has been used to asses and define the accuracy of contour intervals, as in the U.S. map accuracy specifications (Maling, 1989.) A contour line is very similar in concept to the flood extent limit, except that the value is slowly changing (interpolated) from hydraulic transect to transect.

METHODS

The GIS-based simulation of a LIDAR collection for this research involves the simulation of: a) test terrain surfaces, b) the LIDAR data collection, and c) land cover over the terrain. Simplification is part of most modeling approaches. Each of these processes is modeled in a very basic manner attempting only to emulate the fundamental causes of error for of a real LIDAR collection.

There were two reference surfaces created for this study. Both reference surfaces were derived from actual LIDAR data of from opposite banks of Middle Creek in the upper coastal plain near Apex, NC (Figure 4). Each of the study areas are exactly 600m x 800m. The original LIDAR points (x,y,z) were interpolated to a 0.5m X 0.5 meter DEM surface utilizing kriging interpolation. Reference Area 1 (Figure 4) is characterized by very gentle slopes with little local variability. The average slope in Area 1 was calculated as 3.37 degrees and the maximum slope as 29.72 degrees. In contrast Area 2 contains a relatively steep decent into the floodplain and erosion patters have resulted in greater terrain variability. The average slope in Area 2 was calculated as 9.14 degrees and the maximum slope as 83.29 degrees.

The LIDAR data collection was simulated by sampling the test surfaces at successive posting densities (*p)* of 2m, 4m, 6m, 8m and 10m. In each dataset the points were *p* meters apart in both the x any y dimensions. Thus there were almost exactly four times as many points in the initial 2m dataset then in the 4m and so on. These operations resulted in exactly 5 total datasets for each study site.

As discussed previously, two of the main effects of land cover on LIDAR data are data voids, and none-ground points that are mistakenly left in the DEM after the point labeling process. In addition, sensor parameters often introduce uncertainly into the vertical measurement (z) at each LIDAR point. To simulate these effects, datasets were first created from each of the 5 *p* datasets in which random vertical error (*e*) was introduced on the order of 0 cm, 5 cm, 10 cm, 15 cm, and 20 cm. This brought the number of test datasets from 5 *p* to exactly 25 (*p & e)* datasets. Finally, to simulate the effects of data voids, points were removed from each of the datasets in at random. Datasets were created in which none, 25%, 50% and 75% of the points were removed. Thus bringing the total number of test datasets to 100 for each study site. Each of these test LIDAR datasets were stored an ESRI shapefile.

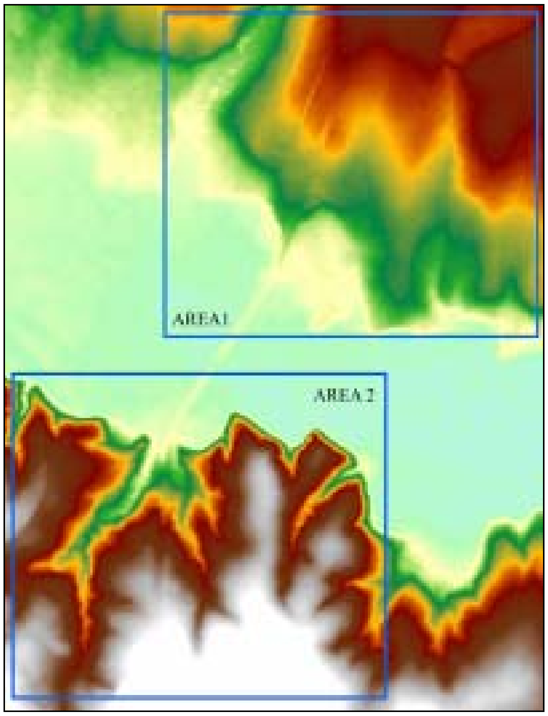


Figure 4 – The relative topography of the each study is depicted.

A triangulated irregular network (TIN) was created form each of the test datasets. TIN interpolation is commonly used for deriving continuous surfaces from LIDAR datasets, particularly in hydraulic applications.

In order to record quantitative information about the *observed* posting density of each dataset, two statistics were calculated on each TIN test surface. The first was the mean distance of every triangle leg in the TIN, and the second was the standard deviation of that mean. The next step was to sample both the reference surfaces and each of the test surfaces and then compute three statistics that would be used to evaluate the accuracy and look for relationship patterns.

The first statistic calculated was vertical RMSE. At the center of each cell in the reference DEM the elevation was extracted from the reference DEM as well as from the TIN surfaces created from each test dataset. The vertical RMSE ($\mathrm{RMSE}_{vertical}$) was then calculated based on the vertical difference between the surfaces.

The second statistic involved examining the difference in surface form between the reference surface and test surfaces. This was accomplished by calculating the angular difference between the local surface normal vectors in both the test surfaces and the reference surface. This was done using a method outlined by Hodgson and Gaile (1999.) These differences were used to calculate an angular error statistic (RMSE_{angle}) for each test surface.

Finally, in order to asses the differences (error) that would result in delineating a flood zone the following process was preformed. Twenty points were sampled at random locations from each test surface. The vertical (z) value of these points was used to draw a contour line on each test surface representing a flood boundary. The minimum distance from the point to the line was recorded and used to calculate a horizontal error ($\mathrm{RMSE}_{horizontial}$) statistic.

RESULTS

The figures on the following page depict the results of the simulation described above. Figure 5 contains the results from the RMSE$_{vertical}$ statistic, Figure 6 the RMSE$_{angle}$ and Figure 7 the RMSE$_{horizontial}$. The numbers along the x-axis represent the amount of points removed from the base of 2m, 4m, 6m, 8m and 10m (to simulate the effects of land cover). As indicated in the figures, the series colors represent the average amount of error introduced to the simulated LIDAR points (representing the effects of sensor and processing error).

In Figure 5 the patter of change for both study areas is very predicable and differs little from what might be expected. The rate at which accuracy changed relative to posting density was different between areas. This result is similar to the findings of MacEachren and Davidson. One interesting item is that in all cases where the number of LIDAR points used to create two surfaces were the same (e.g. 2m with 75% of the points removed and 4m with 0% of the points removed), the more accurate surface was the one with more regularly spaced points. This was more apparent in Area 2 where the surface variability was higher. In order to test the apparent relationship between posting density and vertical error, with the effect of simulated land cover causing data voids, the vertical RMSE was regressed against a linear combination of the mean and the standard deviation of the triangle lengths discussed above. This was done separately for each study area and only using the datasets with no introduced error. The regression equation was of the following form:

$$RMSE_{Vertical} = b0 + b1(\overline{Triangle\_Length} + Stdev_{Triange\_Length})$$

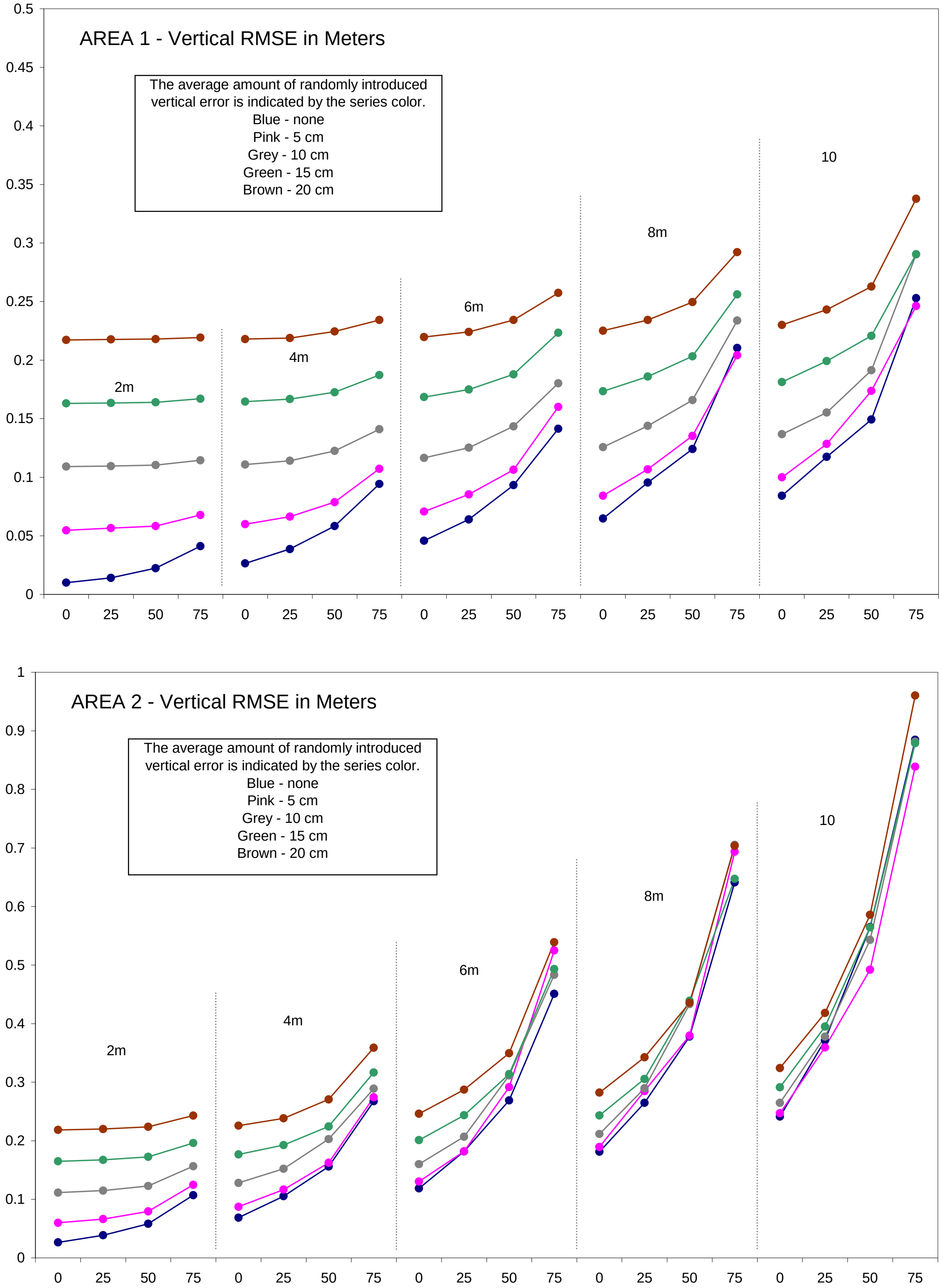


Figure 5a & b – Vertical Error increased at an increasing rate for each posting density and across each simulated land cover. The rate was different in each area, but followed the same pattern.

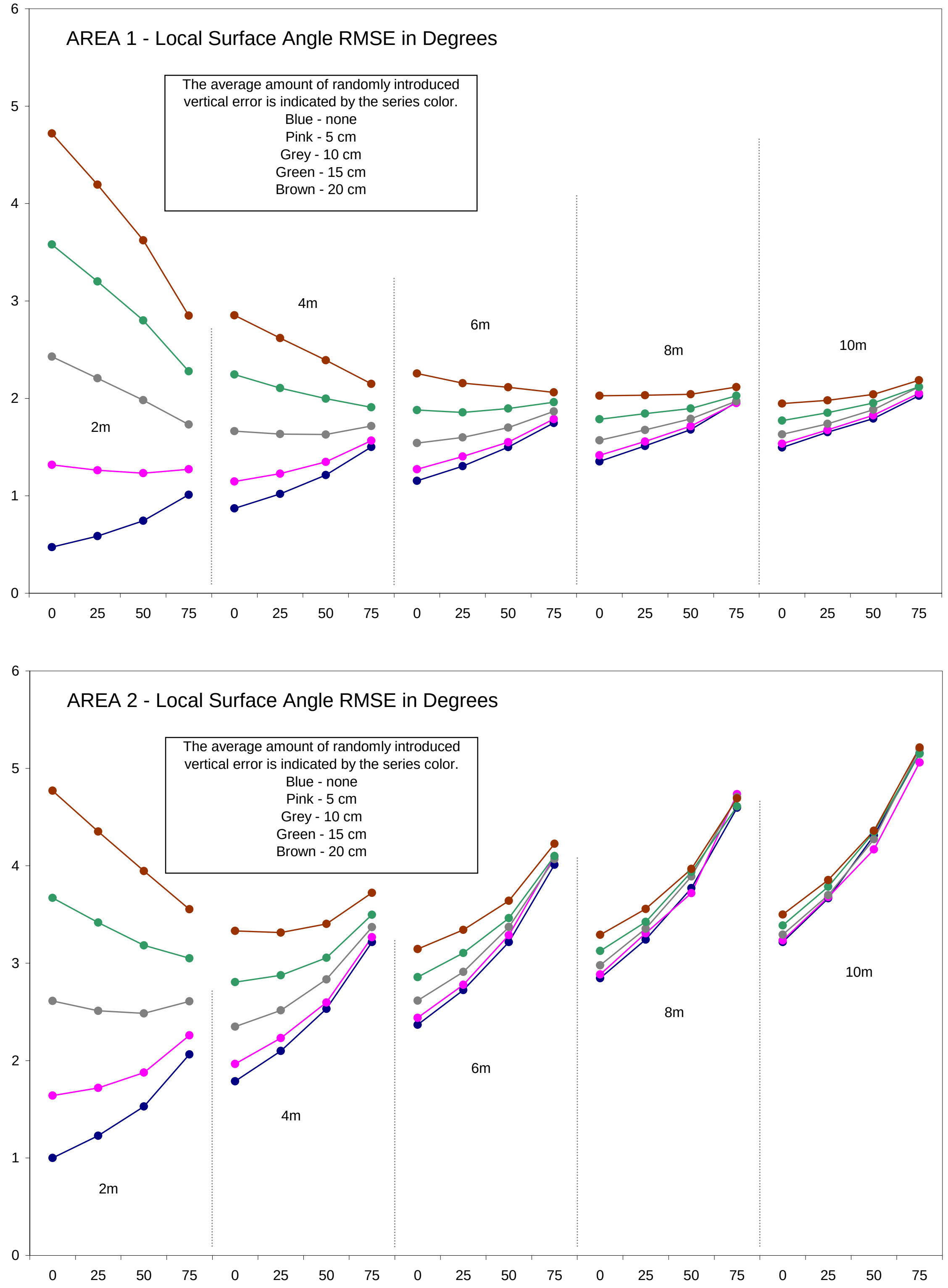
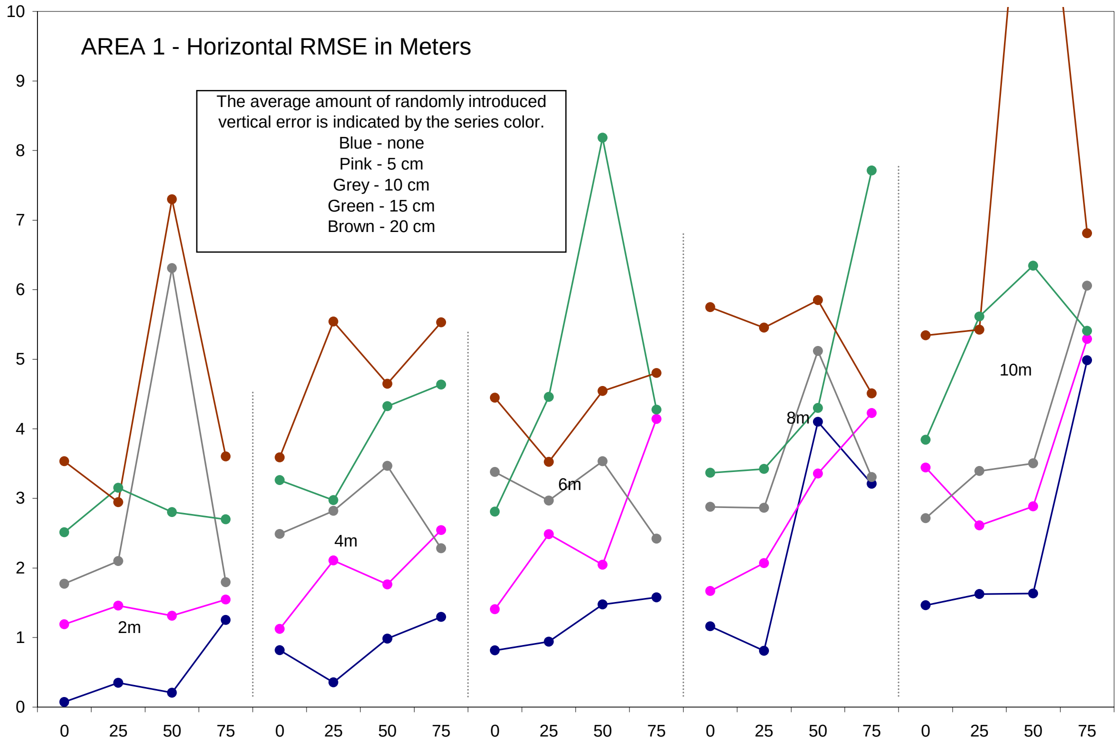


Figure 6a & b – Interestingly, in many cases, particularly when vertical error was introduced, the surface form accuracy actually increased as the points were removed simulating different land covers.



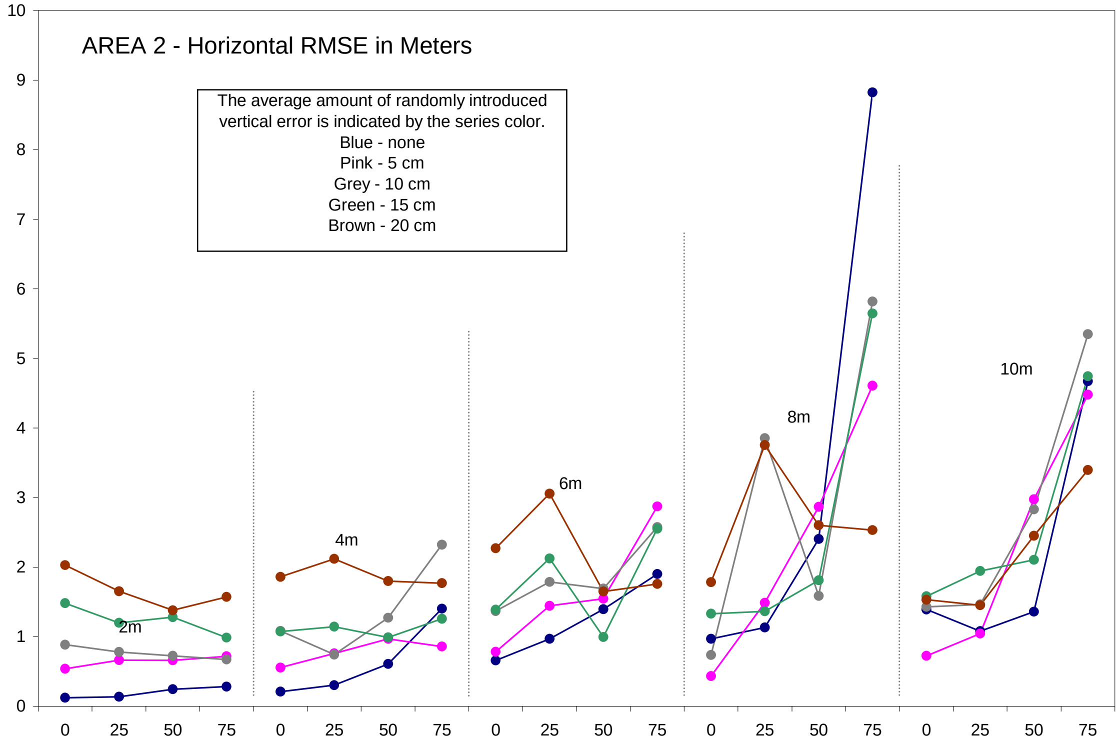


Figure 6a & b – Interestingly, in many cases, particularly when vertical error was introduced, the surface form accuracy actually increased as the points were removed simulating different land covers.

The scatter plots for these equations are shown in Figure 8 a & b. Both had very high r-squared values. In Area 2 the patter of points suggests that the relationship may be non-linear.

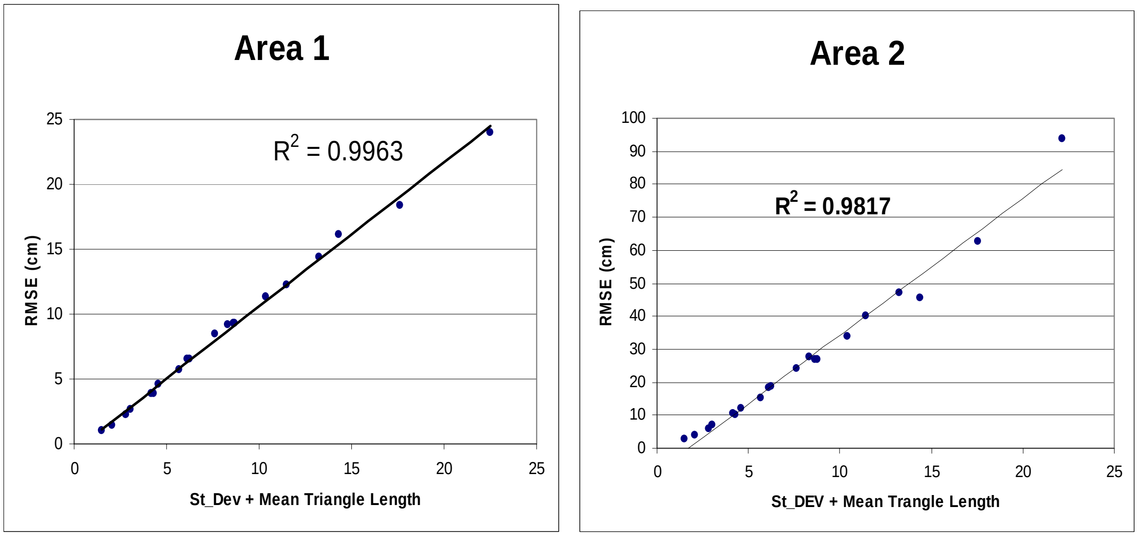


Figure 8 a & b – Scatter plots depicting the relationship between posting density and vertical RMSE.

Figure 6 reveals some very interesting patterns regarding the relationship of posting density with surface form. Surface form accuracy, in some hydrologic applications is often more important then vertical accuracy since it plays a roll in what direction and how quickly water flows across a surface. Perhaps the most significant pattern apparent from the figure is that, in many cases, particularly when vertical error was introduced the surface form accuracy actually increased as the points were removed. This was more apparent in Area 1 where the initial surface form was less variable and in datasets with higher initial posting densities.

Figure 7 shows less encouraging patters then prevalent in the previous figures. However, a recognizable patter does exist if one looks only at the series containing little introduced error. In the 2m initial posting density datasets, the horizontal accuracy appears to be following a similar trend as the surface form accuracy which would make sense based on Equation 5. However, this relationship is not as apparent throughout. Also, particularly in Area 2, the noise in the measurements appears to increase as posting density increases suggesting that variance of this statistic may be increasing at a more regular rate. Testing this theory should be included in future simulations.

CONCLUSIONS

The results of the simulation help to validate the need for an empirical study. The research indicates that it may be possible to predict error in a LIDAR derived surface given some measure of surface variability even if the surface has been sampled at a less then regular interval or points have been removed due to land cover etc. The problem with this approach may be quantifying the surface variability for a given surface. Future research might include a measure of surface variability (fractal dimension, semi-variogram) in the approach. In this way, the potential to develop a regression equation to predict error would be a possibly. This would help interested parties better plan LIDAR mission parameters to match target accuracy requirements.

It would be very interesting if similar surface form patterns were observed in an empirical study as in the simulation. If this were the case, it would indicate that careful thought would have to be taken in planning LIDAR missions involving surface form dependent applications.

Although the connection between vertical accuracy was not strong in this case, there was a general pattern apparent. Perhaps running a Monte Carlo type simulation, and thereby increasing the number of samples, would yield a better result. Future research should also include looking at the variance of the horizontal statistic as it likely increases at a more regular rate.

Another topic of future research would be to refine the simulation to include additional aspects of a LIDAR collection as the simulation attempted herein was perhaps oversimplified. A more complex simulation might also include an actual hydraulic model so an attempt on observing changes to the flood stage could also be made. Figure

9 is a flow diagram of the proposed GIS LIDAR simulator. Of course, performing an empirical study to validate the results is also of great importance.

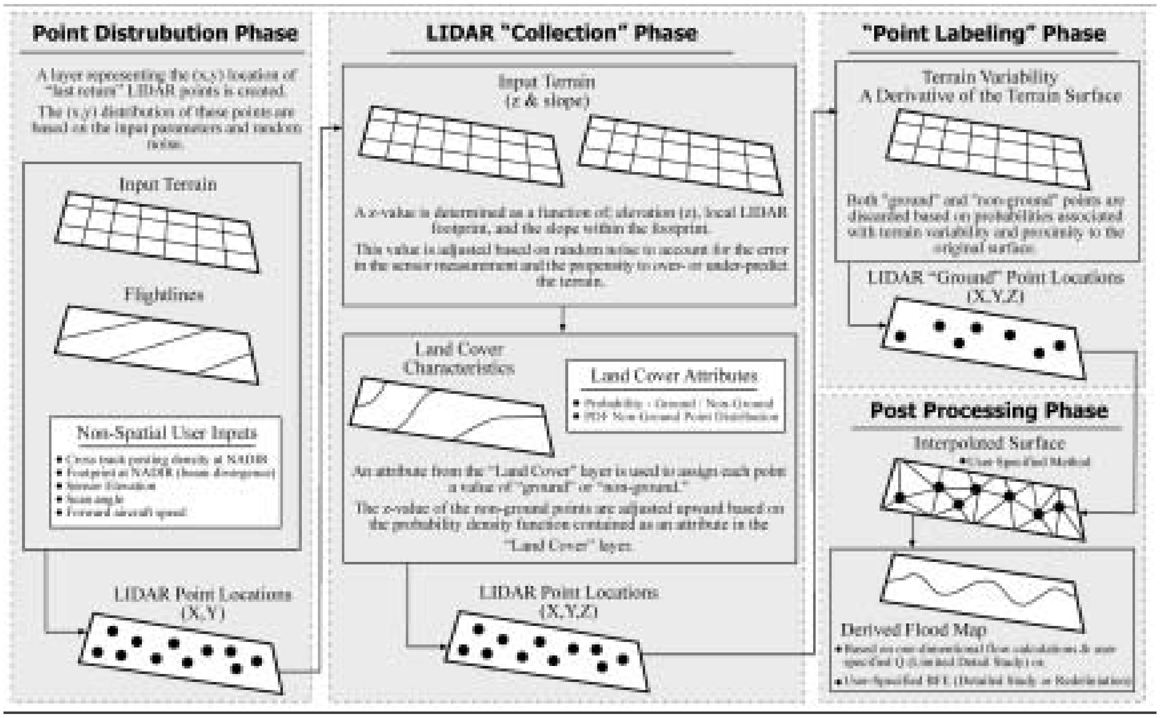


Figure 9 – Flow diagram for a proposed GIS-Based LIDAR Collection Simulation System

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REFERENCES

Bates, P.D. and A.P.J. De Roo, 2000, A Simple Raster-Based Model for Flood Inundation Simulation, *Journal of Hydrology*, 236:54-77.

Buckley, Michael, 2001, *Policy for Use of HEC-RAS in the NFIP,* FEMA, Memorandum for Hazards Study Branch, Regional Engineers, and Map Coordination Contractors, URL: http://www.fema.gov/mit/tsd/frm_hrpy.pdf

Bolstad, P. 2002, GIS Fundamentals, Eider Press, White Bear Lake, MN, 411p.

Bolstad, P.V. and T. Stowe, An Evaluation of DEM Accuracy: Elevation, Slope and Aspect, *Photogrammetric Engineering and Remote Sensing,* 60(11):1327-1332.

Bowen, Z.H and R.G. Waltermire, 2002, Evaluation of Light Detection and Ranging (LIDAR) for Measuring River Corridor Topography, Journal of the American Water Resources Association, 38(1):33-41.

Box, David, 2001, Personal Communication

Cobby, D.M. D.C Mason, and I.J. Davenport, 2001, Image Processing of Airborne Scanning Laser Altimetry for Improved River Flood Modeling, *ISPRS Journal of Photogrammetry and Remote Sensing*, 56:121-138.

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 and Remote Sensing,* 66(11):1323-1326.

Chow, T.E., 2001, Sensitive of Modeled Peak Discharge to LIDAR Post-Spacing, Columbia, University of South Carolina, Masters Thesis, 68 p.

Chow, V.T., 1959, *Open Channel Hydraulics*, McGraw-Hill, Inc., New York, NY, 680 p.

Dunn, R. A.R. Harrison, and J.C. White, 1990, Positional Accuracy Measurement in Digital Databases of Land Use: An Empirical Study, *International Journal of Geographical Information Systems*, 4:385-398.

Edwards, G. and K.E. Lowell, 1996, Modeling Uncertainty in Photointerpreted Boundaries, *Photogrammetric Engineering & Remote Sensing*, 62(4)377-391.

Fisher, P.F., 1992, First Experiments in Viewshed Uncertainty: The Uncertainty of the Viewshed Area, *Photogrammetric Engineering and Remote Sensing,* 57(10):1321-1327.

Hodgson, M.E., J.R. Jensen, L. Schmidt, S. Schill, and B. Davis, 2003a, 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*, *In press*

Hodgson, M.E., J.R. Jensen, G. T. Raber, J.A. Tullis, B. Davis, K. Schuckman, G. Thompson, 2003b, A Comparison of LIDAR-Derived Elevation and Slope Accuracy in Leaf-On and Leaf-Off Conditions, *Photogrammetric Engineering and Remote Sensing, Submitted*

Hodgson, M.E., and P. Bresnahan, 2003, Accuracy of Airborne LIDAR Derived Elevation: Empirical Assessment and Error Budget, *Photogrammetric Engineering and Remote Sensing, Submitted*

M.E. Hodgson and G. L. Gaile, 1999, A cartographic modeling approach for surface orientation-related applications, *Photogrammetric Engineering and Remote Sensing*. 65(1): 85-95.

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.

Leung, Y. and J. Yan, 1999, A Locational Error Model for Spatial Features, *International Journal of Geographical Information Systems*, 12(6):607-620.

Liu, J.S., 2001, *Monte Carlo Strategies in Scientific Computing*, Springer, New York, NY, 343p.

MacEachren, A. M., and J. V. Davidson, 1987, Sampling and Isometric Mapping of Continuous Geographic Surfaces, *The American Cartographer*, 14(4) 299-320.

Maling, D.H., 1989, *Measurement from Maps*, Pergamon Press, New York, NY, 577 p.

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 (ASPRS), Bethesda, MD, 539 p.

Raber, G. T., J. R. Jensen, S.R. Schill, K. Schuckman, 2002, Creation of Digital Terrain Models Using an Adaptive LIDAR Vegetation Point Removal Process. *Photogrammetric Engineering & Remote Sensing*, 68(12)1307-1315.

North Carolina Floodplain Mapping Program, 2002, URL: http://www.ncfloodmaps.com/

NRC (National Research Council), 2000, *Risk Analysis and Uncertainty in Flood Damage Reduction Studies*, Committee on Risk-Based Analyses for Flood Damage Reduction, National Academy Press, Washington, DC.

FEMA (Federal Emergency Management Agency), 2002, Map Modernization Objective: Automated Hydrology and Hydraulics (H&H) Floodplain Mapping, URL: http://www.fema.gov/mit/tsd/mm_ahh6.htm

USACE (United States Army Corps of Engineers), 1986, *Accuracy of Computed Water Surface Profiles*, Research Document 26, Hydraulic Engineering Center (HEC), Davis, CA.

USACE (United States Army Corps of Engineers), 1996, *Risk-Based Analysis for Flood Damage Reduction Studies*, Manual, EM 1110-2-1619, Washington, DC.

USACE (United States Army Corps of Engineers), 2001, *HEC-River Anaysiys System Hydraulic Reference Manual v3.0*, Manual, CPD-69, Hydraulic Engineering Center (HEC), Davis, CA.

Wolock, D.M and C.V. Price, 1994, Effects of Digital Elevation Model Map Scale and Data Resolution on a Topography-Based Watershed Model, *Water Resources Research*, 30(11):3041-3052.

Zang, W and D.R. Montgomery, 1994, Digital Elevation Model Grid Size, Landscape Representation and Hydrologic Simulations, *Water Resources Research*, 30(4):1019-1028.