Comparison of 10m NED and LiDAR DEM Error in the Context of Critical Dune Management on the Lake Michigan Shoreline

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Abstract

Michigan laws forbid landscape modifications in dune areas with slope over 33%, and restrict modifications in 25%-33% slope. Currently, a critical dune site assessment tool developed by the Remote Sensing and Geographic Information Science Program at MSU uses 30m elevation data to determine slope for granting building permits. However, high errors in the 30m dataset lead us to investigate LiDAR (U.S. Army Corps of Engineers) and the 10m USGS DEM as possible alternatives. The elevation datasets were processed into drop grids and Arc Markup Language (AML) code was used to simulate error based on ground truth GPS points, then give output grids ranging from 0 (no simulations show critical slopes) to 100 (all simulations show high slope). These output grids were compared to the ground truth to show how well they simulated error and slope. For the most part, the LiDAR simulations correspond with well with actual ground slope. However, some high error in low slope areas as well no general correlation in the 10m dataset leaves some issues to be dealt with. It is possible that this slope model does not best portray local topographic variation, or that there may be unusually high error in the elevation datasets at certain areas or in the ground truth points. Overall, propagating error through the data gives users a range of confidence that can be considered for their decisions based on elevation derivatives, and is a powerful tool for justifying those decisions.

I. Introduction

Digital elevation models (DEMs) provide valuable information about earth's characteristics that are useful in policy implementation. Digital terrain models have been employed in the evaluation of suitable locations for building and landscape modification along the coasts. Of particular interest is the use of digital elevation models in evaluating the topography of dunes located along the Lake Michigan shoreline. A critical dune site assessment tool has been developed by the Remote Sensing and Geographic Information Science Outreach Program at Michigan State University to aid users in ensuring that any landscape modification follows critical dune laws pertaining to slope. Currently the law prohibits the following:

(a) A structure and access to the structure on a slope within a critical dune area that has a slope that measures from a **1-foot vertical rise in a 4-foot horizontal plane to less than**

a 1-foot vertical rise in a 3-foot horizontal plane, unless the structure and access to the structure are in accordance with plans prepared for the site by a **registered professional architect or a licensed professional engineer** and the plans provide for the disposal of storm waters without serious soil erosion and without sedimentation of any stream or other body of water. Prior to approval of the plan, the planning commission shall consult with the local soil conservation district.

(b) A use on a slope within a critical dune area that has a **slope steeper than a 1-foot vertical rise in a 3-foot horizontal plane.**

(Michigan State Legislature, Act 451(1994):353, 324.35316(1)).

Currently, the tool uses 30m (1 arc second) DEMs; however, the errors in the 30m slope derivative are very high (Bookout, 2006). Thus, the purpose of our project is to determine whether 10m (1/3 arc second) or LiDAR slope is more reliable than the 30m DEM in the context of decision making, and how error propagates through these datasets.

Our study area runs along 8.73 kilometers of shoreline and about 300 meters inland, in Berrien County, Michigan (Figure 1). Viewing the DEMs, it is clear that this area contains a large number of dunes, as there are many linear features along the shore. Moreover, the gently rising face of the windward side, and the steep slopes of some of the slipfaces (leeward side) of the dunes are visible on the LiDAR dataset.

II. Methods

The creation and comparison of drop grids for decision-making mostly involved basic commands to evaluate the ground truth and our data sources. The following methods are based upon GPS ground truth data, LiDAR Data, and 10m DEM data. The 10m DEM and LiDAR sources are shown in Figure 2. A subset of the LiDAR data is indicated to show the greater detail in comparison to the coarser 10m elevation data. The ground truth consisted of 47 GPS points collected in Berrien County, which includes information about GPS elevation, slope and aspect (Bookout, 2006). The GPS elevation points were largely ignored for two reasons: they tend to have higer z error than the x, y coordinates (Shortridge, 2006), and we were more interested in slope error, rather than elevation error.

Our overall process is summarized in Figure 3. The ground truth points were converted to drop points in the following manner: the aspect values were rounded to the nearest 45 degree value (i.e. rooks case or bishops neighbors). Rooks case indicates direct neighbors, while bishops neighbors indicate diagonal neighbors. In order to compare the drop error to each grid (LiDAR and 10m), the drop was solved for by multiplying the percent slope by 100, then dividing by the run, which was equal to the cell size in the rooks case neighbor, or 1.414 times the cell size for the bishops case neighbor (which were "inter-cardinal" directions). These points were then imported into ArcGIS 9.1 (ESRI, 2005) and converted into a grid of "ground truth" drop values.

The LiDAR dataset came as unevenly spaced points extending along the length of the Berrien County shoreline in a strip roughly 300 meters wide. We selected a portion of LiDAR points along the shoreline that contained the ground truth points. Then, the points were interpolated into a 2m by 2m resolution grid using the inverse distance weighting (IDW) method, with a power setting of 3.05 and 9 neighbors (as per Bookout, 2006).

The NED 10m data was already in raster format, and was simply clipped to the boundary of our study area. The elevation grids were converted into drop grids (Figure 4) by our drop conversion AML code (Figure 5). The drop grid (Figure 4) of the LiDAR dataset resembles a percent slope grid, while the drop of the 10m DEM has a smoother appearance. Essentially, the drop is calculated as the greatest change in elevation from one of the 8 neighbors to the centroid of the kernel.

The ground truth drop was then subtracted from the drop grids of the LiDAR and 10m drop to achieve a meaningful root mean square error (RMSE), since the scale of the percent slope values change by orders of magnitude of the drop. Of the available 47 ground truth points, only 46 points were located in the extent of the LiDAR data, and 45 in the 10m DEM. Also, the standard deviation and Moran's I (a measure of spatial autocorrelation) values (both needed to created error realizations) were calculated. The Moran's I values range from -1 to 1, where -1 indicates negative spatial autocorrelation and 1 indicates positive spatial autocorrelation.

Next, we used looping error propagation AML script to create error realizations, smooth them to the parameters of the drop grid (approximately the standard deviation and Moran's I). The LiDAR and 10m error realizations were smoothed by a circular focalmean of 6 and 5 cell radiuses, respectively. These realizations were added to the drop grids. The error was simulated 100 times on both the LiDAR and 10m drop grids, with slope as the final calculation to determine site suitability for each realization (Figures 6 and 7). The error propagation simulations indicate confidence of the DEM related to the critical slope cutoffs.

III. Results

Table 1 shows the descriptive statistics of the LiDAR DEM, 10m DEM, LiDAR drop, and 10m drop grids. The range, mean, and standard deviation of the 10m DEM and drop grids are higher in comparison to the LiDAR grids.

We ran the suitability AML script with the embedded slope calculation (Figures 6 and 7) 100 times in order to determine the impact of error on the slope determination of our study area. This means that the slope was recalculated for each error realization. The outputs (33% and 25%-33% grids) represent the total number of times a cell was suitable for the given criteria (Table 2). Generally, where slope was higher there were higher values in the suitability grids. This is different than a strict reclass of a standard slope grid of the LiDAR DEM, which does not take error in the data into account. An example of this is in Figure 8, where the error propagation map looks much fuzzier than the straight reclass. These were located very close to the shoreline of the study region for the 10m DEM. However, the suitability output for the LiDAR DEM greater than 33% was more widespread across the study area. This was likely a result of the different cell resolutions of the DEMs. The percent of 50% (50 out of 100 realizations) was chosen as a confidence level for identification of a cell that was greater than 33 % based on the ground truth slope. The slope grids were reclassed according to this value to indicate locations where sites have greater than 33 % slope. Similarly, the 25%-33% suitability and both LiDAR and 10m grids were reclassed at their 50th percentile (Figures 9 and 10).

To verify the decisions with reality, the ground truth slope was compared to the output of the suitability grid. Essentially, the ground truth slope was graphed versus the number of realizations with a critical slope value (33%+, etc.). It was expected that the slope cutoff decisions would match our ground truth, but that wasn't always the case. The lowest LiDAR suitability value at a location with an actual slope over 33% was 2/100 realizations, followed by 13/100. Also, only two of the ground truth points gave significant results in the 10m output. For one point that was over 33% on the ground truth, it gave a suitability of 1/100. Also, one ground truth point that was below 33% occurred as over 33% slope in the realization 68 times. Figures 11a and b shows how the number of error propagations with certain slope correlates with the ground truth slopes. Generally, the number of realizations showing 25%-33% slopes peaks in the middle of that range (shown by the trendline) as it should. However, the 33%+ slope realizations shows a high number of error realizations in low slope areas, with a decrease around

20%, and then a growing trend. We would expect almost no error realizations to show high slope in actual low slope areas.

IV. Discussion

The slope-error realization aspect of the project has great implications in terms of accounting for error in slope determinations in the permit-granting process. In order to decrease the time it takes for the field measurements of the slope, the slope-error realizations indicates at what level of confidence certain locations can be determined as too steep for development.

A simple reclass of a slope grid yields little meaningful results, especially where the slope is near the cutoff point. This is because minor error in the DEM would affect the actual suitability output the computer would calculate. It is true that our suitability grids (Figures 9 and 10) match up closely with slope. However, the power of this analysis is that a user can query a point of interest (for example, a prospective building site) and determine the chances of the slope being over 33%. If they find the odds to be 98% against them, it might be wise to find another location.

At first glance, the comparison of the suitability versus ground truth is troubling. However, the results from the LiDAR 33% suitability that gave 2/100 or 13/100 as their probability correspond to a slope of 34% in real life. In fact, the ground truth slopes don't consistently go over 40% until the output of the suitability AML is over 33/100. There are some anomalous results however, where the ground truth slopes and suitability results do not seem to match. This is especially true in the 10m DEM, whose suitability results seem to have little bearing on reality (i.e. lots of high ground truth slope with 0/100 as the AML output). This leads us to believe that our process either does not capture local topography correctly in all areas, the data source error was unusually high in those areas, or that the ground truth slope was flawed. For example, a highly variable, hummocky area with a flat slope may not be accurately interpolated on the LiDAR DEM. Smoothing and drop operations that act over several cells may lose that information. The results may be worse for the 10m DEM (Figure 11b), which shows little correlation between realizations and ground truth.

V. Conclusion

Implementation of policy that requires field checking information can put high demand on agencies with limited resources for such activities. As such they are hoping to rely on digital data to help make decisions remotely. As of now, elevation and slope datasets have inherent error that is difficult to measure or interpret for decision making purposes. It is generally assumed that high slope areas on a DEM probably correspond to areas of high slope in reality, but the error is hard to quantify.

Our method of calculating slope removes elevation error biases and also provides steepest slope, which help alleviate slope errors in highly variable environments. Thus, by calculating the slope on local drop grids with added drop error as opposed to elevation error, a percent likelihood of suitability or unsuitability is output. The resultant grid is easy to understand, as it is scaled from 1 to 100, with 100 being a near certain chance that that area is over 33% slope (or 25%-33%). This gives agents a real number of their confidence in their decisions based on digital data.

Given our analysis, it is still the user's responsibility to decide where the proper cutoff between reliable and unreliable is. More ground truth points to compare with the output may aide in establishing this cutoff. We hope that if the DEQ has better knowledge about errors in their DEMs they may make more accurate decisions based on the digital data. It is also the recommendation of this study that they continue to invest in LiDAR based data, as the 10m DEM tends to show high error in dune areas.

VI. Figures

Figure 1. Study Area

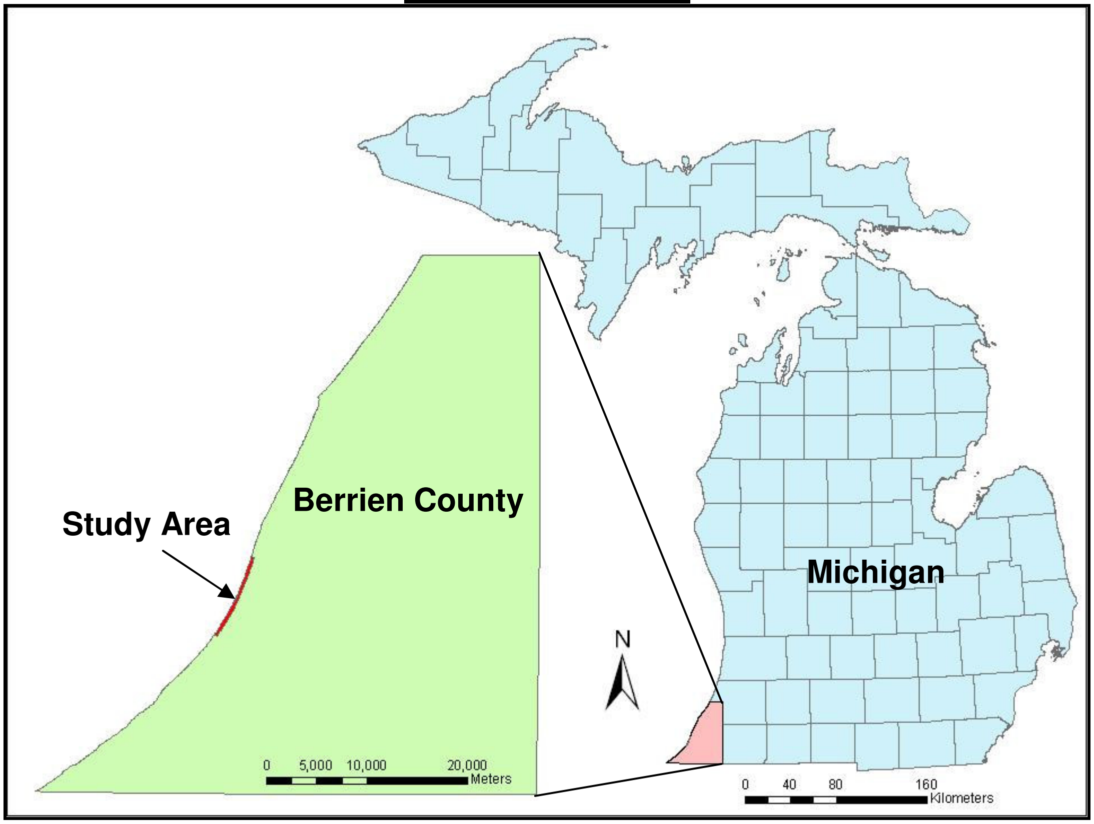


Figure 2. Data Sources

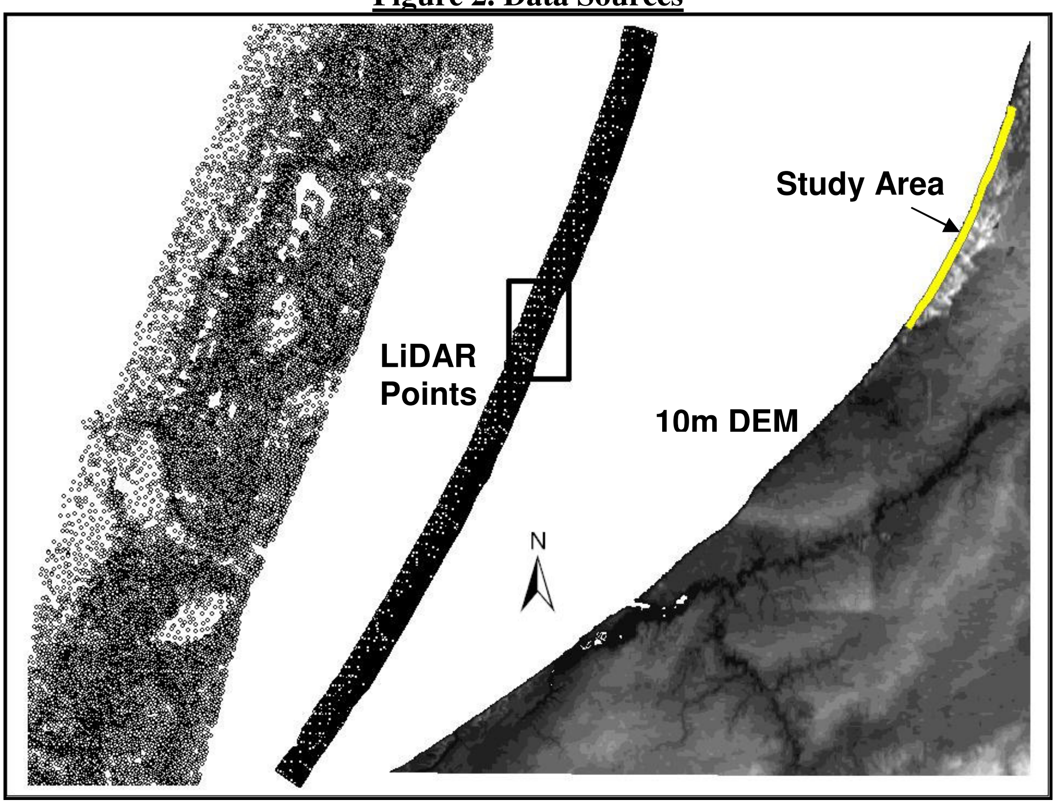


Figure 3. Project Flow Chart

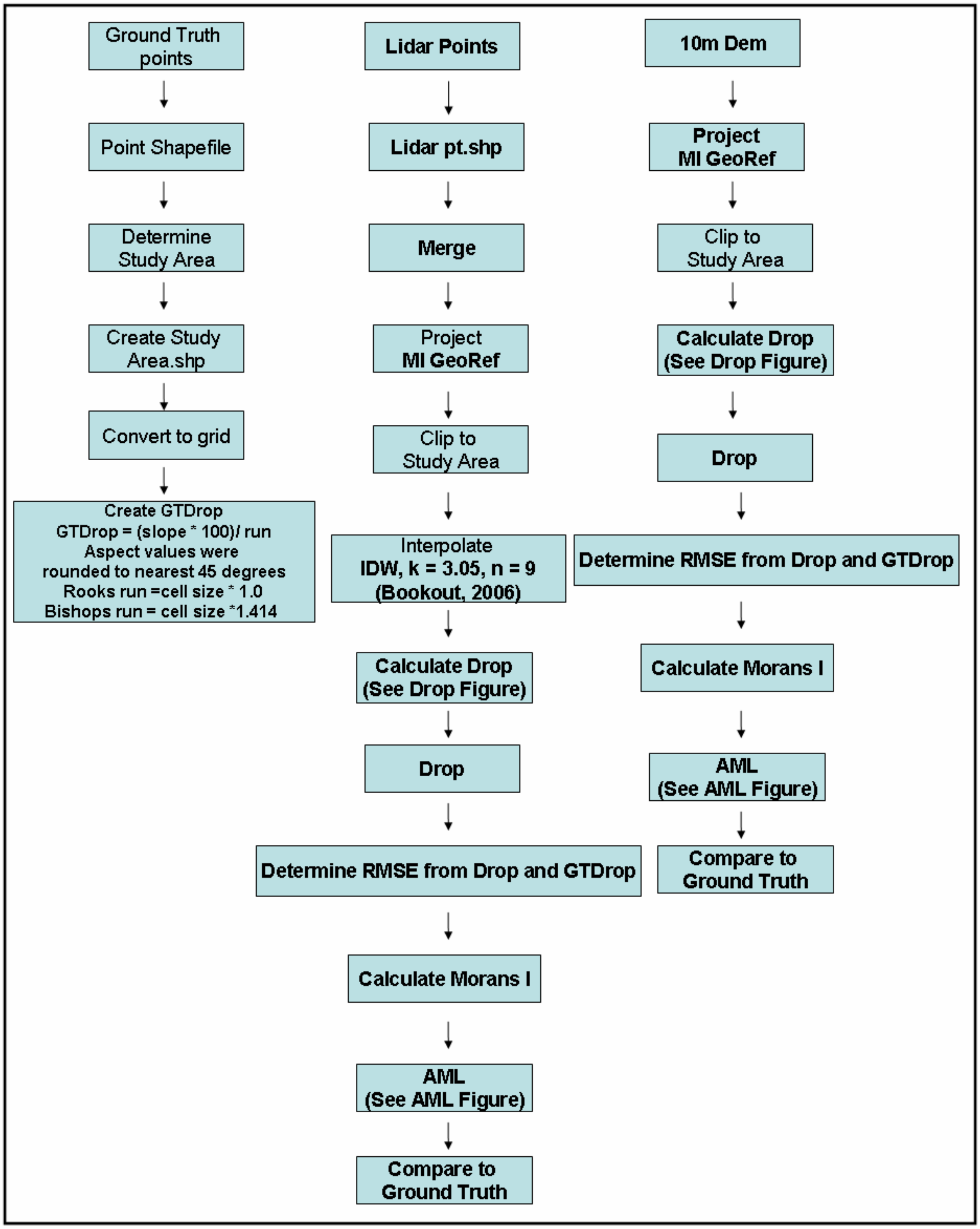


Figure 4. Comparison of LiDAR and 10m DEM, Elevation and Drop

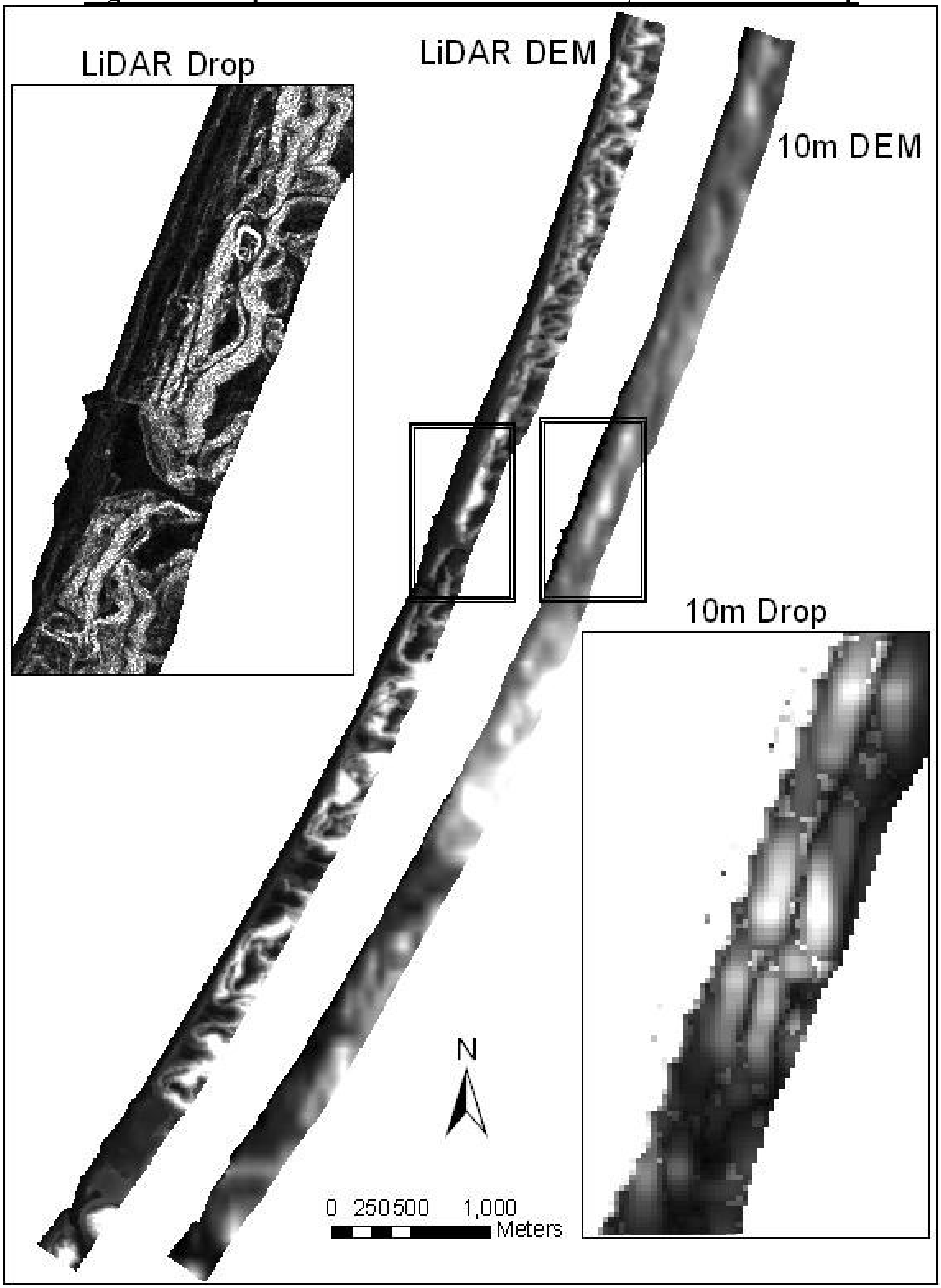


Figure 5. Drop AML Flow Chart

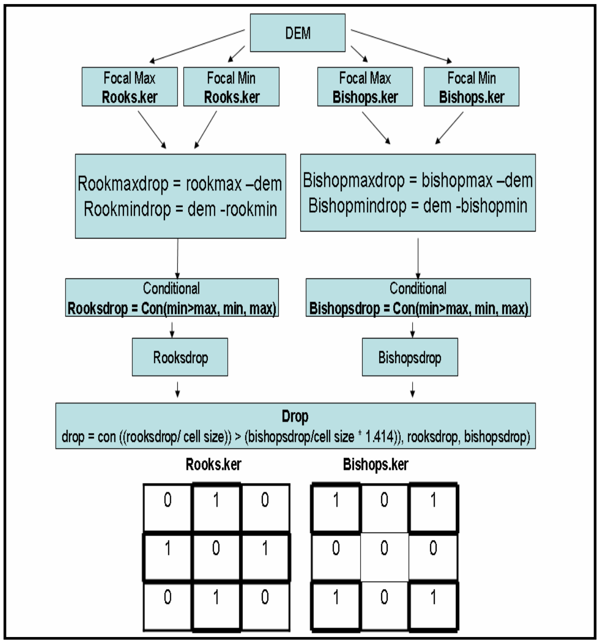


Figure 6. Slope AML Flow Chart

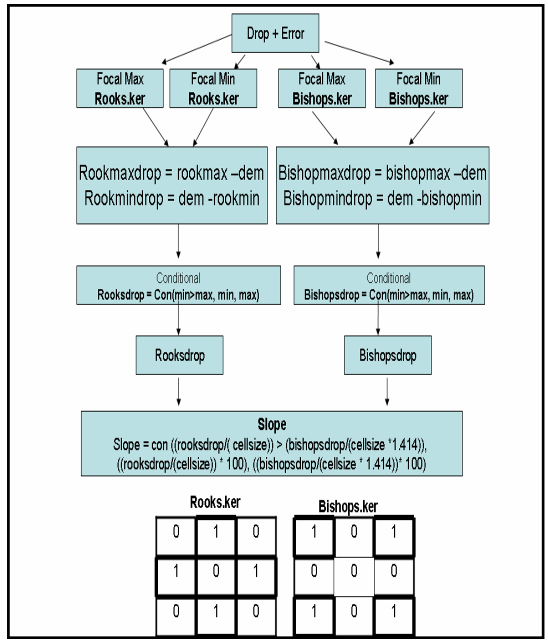


Figure 7. Error Propagation and Suitability AML Flowchart

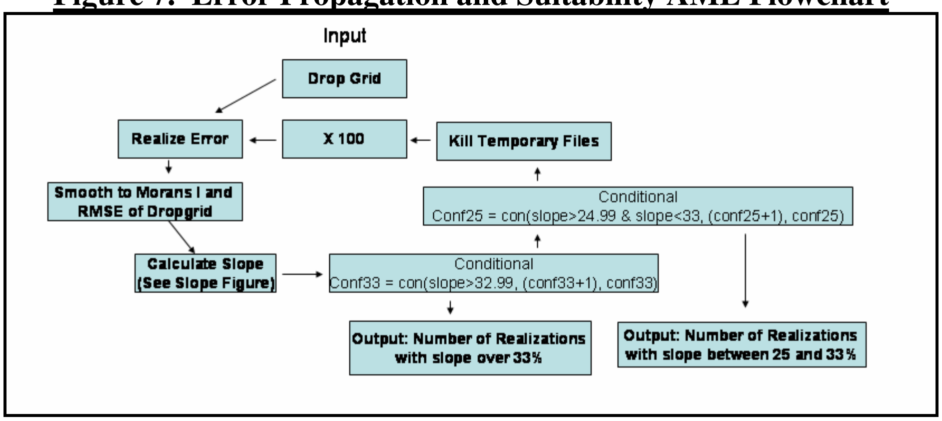


Figure 8. LiDAR Error Propagation Decision vs. LiDAR Slope Decision

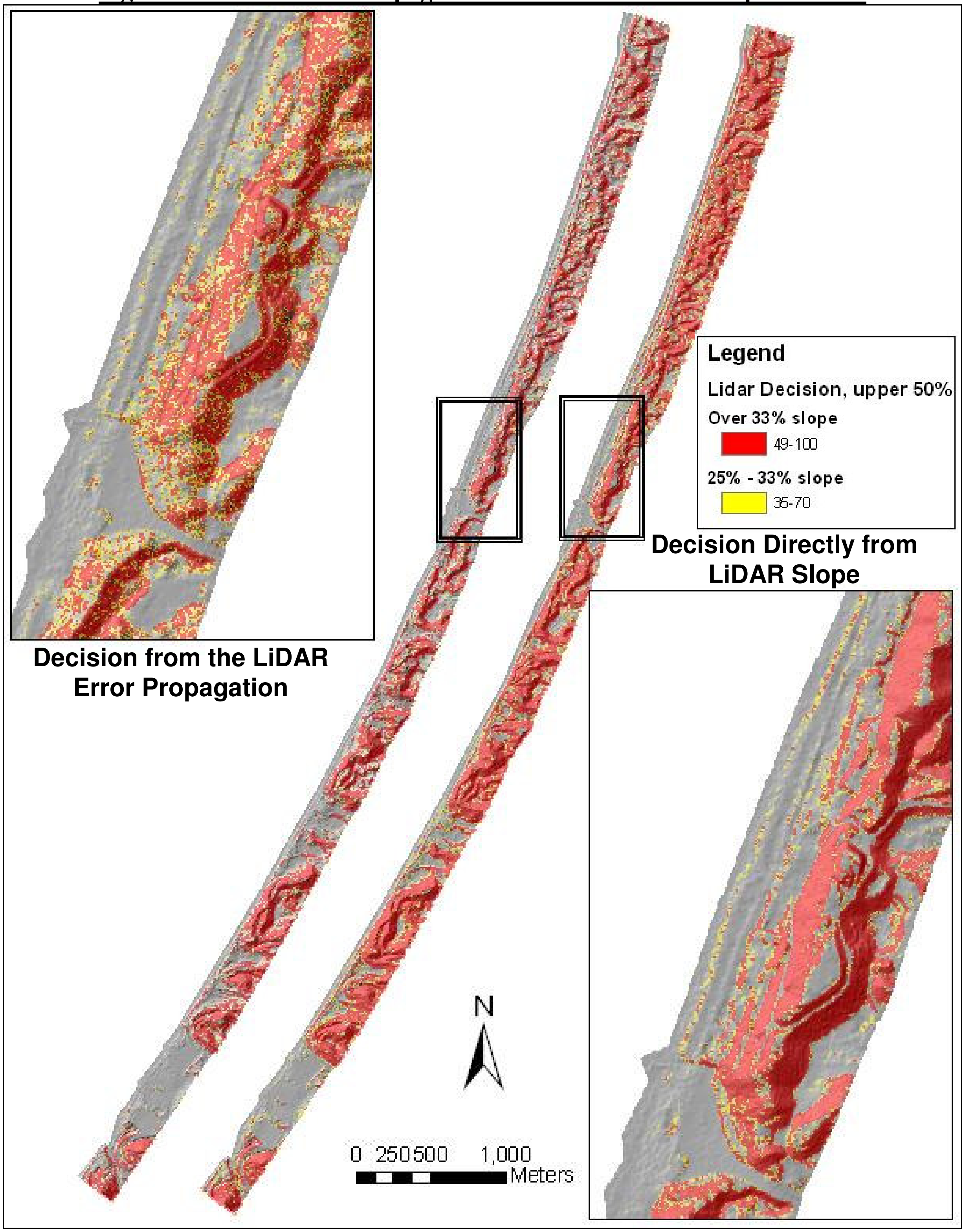


Figure 9. Reclassed Decision output from LiDAR

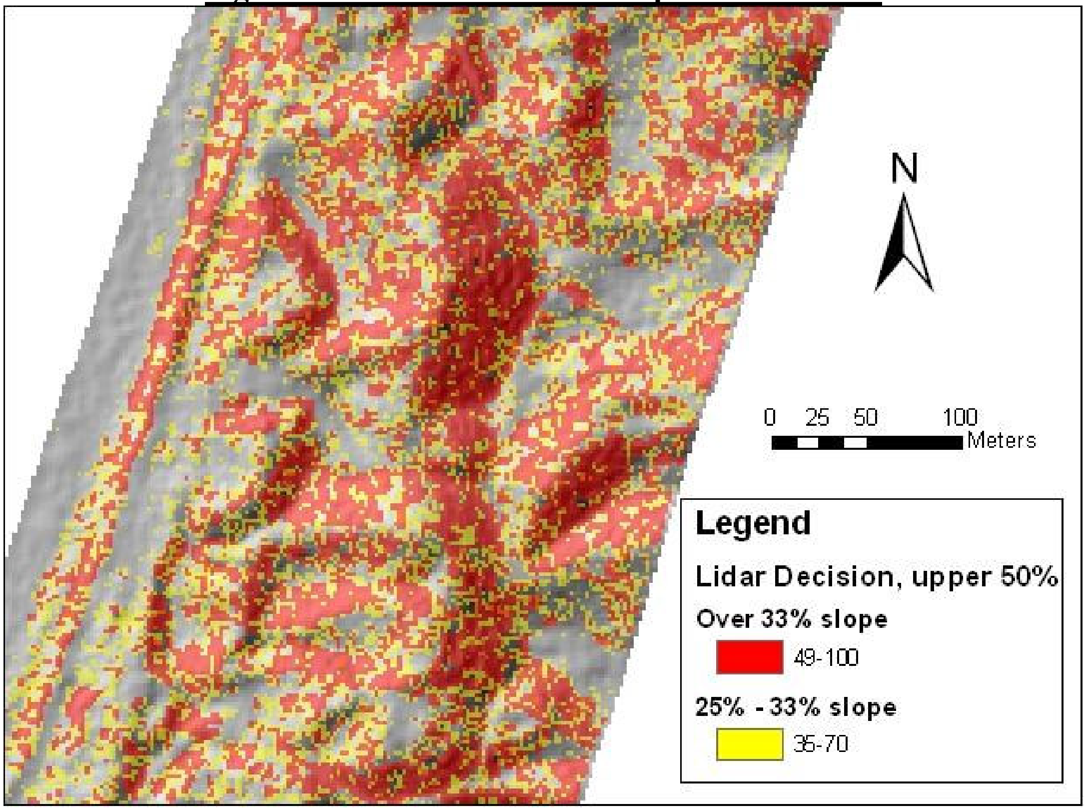


Figure 10. Reclassed Decision output from 10m DEM

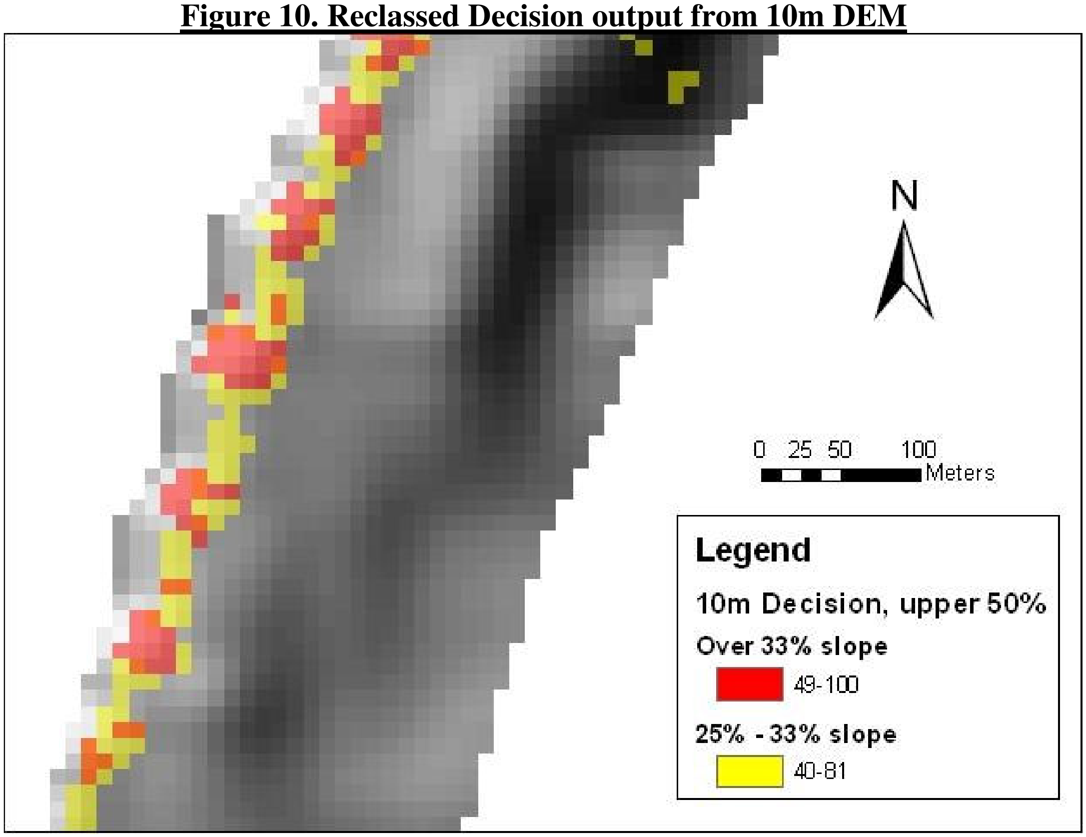
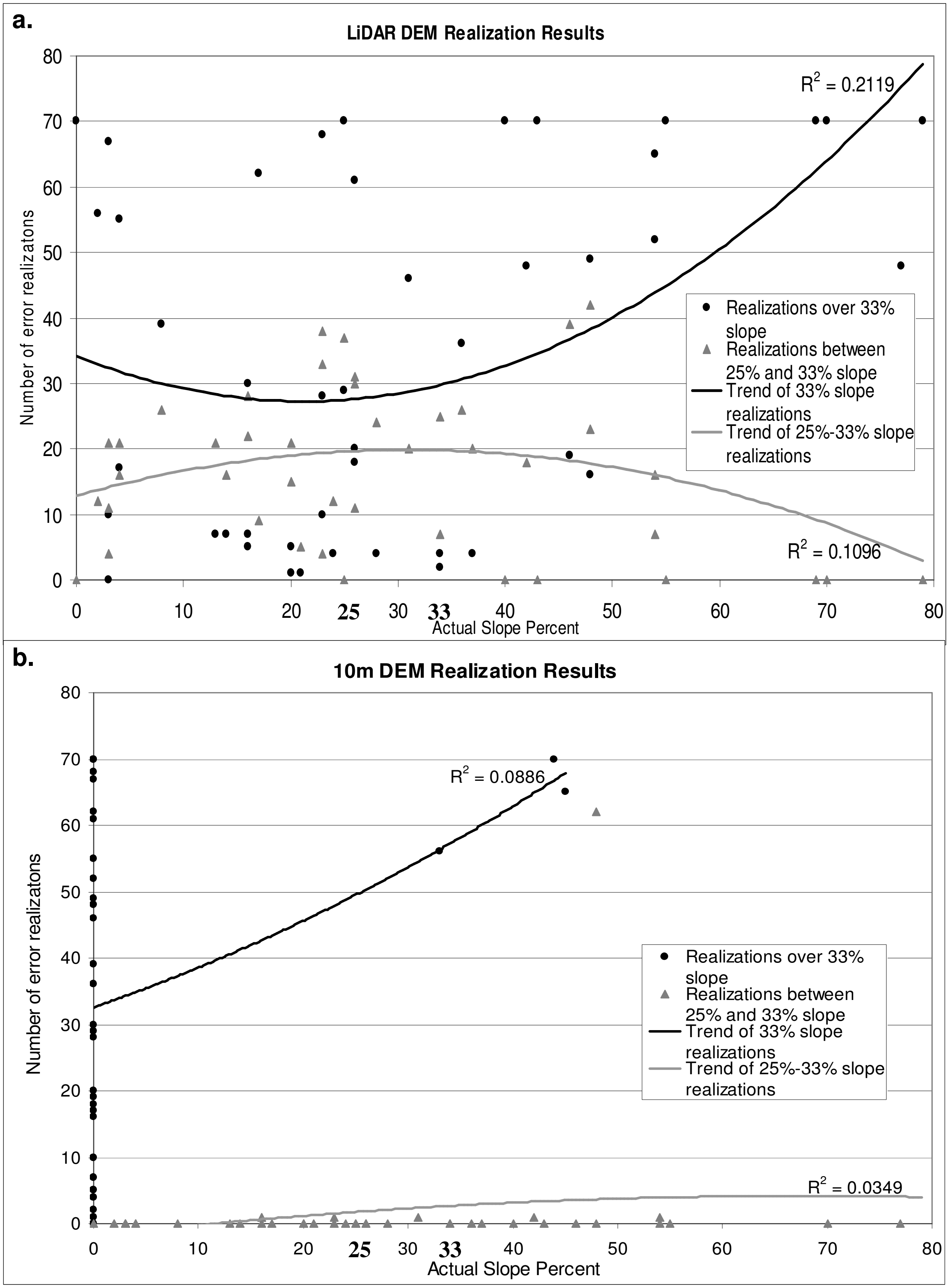


Figure 11. Realization Decision Results vs. Actual Slope



VII. Descriptive Statistics

Table 1. LiDAR and 10m DEM Descriptive Statistics

	LiDAR DEM	10m DEM	LiDAR Drop	10m Drop
Cell Size	2	10.0	2	10.0
Rows	4025	805	4025	805
Columns	1900	398	1990	398
Range (m)	176.101-232.700	176.486-247.731	0-8.356	0.059-15.077
Mean (m)	189.608	204.958	0.849	1.748
Standard Deviation (m)	9.461	11.546	0.634	1.265
RMSE			0.352	2.789
Moran's I			0.805	0.816

Table 2. Percent Slope AML Outputs

Suitability Grid	LiDAR 33	LiDAR 25-32	10m 33	10m 25-32
Cell Size	2	2	10	10
Rows	4025	4025	805	805
Columns	1990	1990	398	398
Range	0-100	0-70.0	0-100.00	0-81.0
Mean	41.041	23.143	1.495	2.387
Standard Deviation	36.904	14.509	10.202	8.985

VIII. Sources

Bookout, J.R. 2006. 47 Ground Truth Points. Shapefile. From "Using Digital Elevation Data to Predict Slopes of Coastal Sand Dunes in Berrien County, Michigan." Master's Thesis, Michigan State University, East Lansing, MI. Unpublished.

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Shortridge, A. 2006. Geography 428: Digital Terrain Analysis. Lecture notes, September 15th, 2006.

United States Army Corps of Engineers. LiDAR point collection. X,Y,Z Text Berrien County, Michigan.

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