Storm water damage risk assessment along the South Carolina Heritage Trail

C. Alex Pellett¹, David White², Patrick McMillan³, Dara Park⁴, William Bridges⁵

AUTHORS: ¹Grad Student, Clemson University, C227 Poole, Clemson, SC 29634-0317, USA. ²Director of Environmental Informatics, Clemson University, 2101 Barre Hall, Clemson, SC 29634-0317, USA. ³Director, SC Botanical Garden, 261 Lehotsky Hall, Clemson, SC 29634-0317, USA. ⁴Soil and Water Specialist, Clemson University, 273 Poole, Clemson, SC 29634-0317, USA. ⁵Professor of Mathematical Sciences, Clemson University, O-117 Martin Hall, Clemson, SC 29634-0317, USA.


ABSTRACT. Storm water damage in the form of rill formation across the South Carolina Botanic Gardens (SCBG) Heritage Trail has been modelled as a function of contributing area using D8 and D-infinit flow direction algorithms on a preprocessed LiDAR-derived elevation raster. D8 and D-infinit algorithms were also applied over a set of stochastic Monte Carlo simulations (n=1,000) representing elevation error. The contributing area was calculated using each of the four methods for each 5'x5' cell along the trail. The output was then filtered with a moving kernel calculating a value for each cell according to the maximum value within specified radii of neighboring cells. Observed storm water damage along the trail was geo-referenced as a validation dataset for the model. The receiver operating characteristic (ROC) curves of the three contributing area estimates filtered at various filter radii were graphed by comparison with geo-referenced rills. Results indicate that high resolution LiDAR elevation data can be used to localize storm water damage risks. The D-infinit algorithm performed better than the D8 algorithm, and the Monte Carlo procedure improved the results of both.

INTRODUCTION

Since the South Carolina Heritage Trail was opened to the public in spring 2014, several intense storm events have led to rill formation along its length. The South Carolina Department of Natural Resources has made high resolution Light Detection and Ranging (LiDAR) elevation data available to the public (SCDNR, 2014). This elevation data has great potential for modelling surface hydrology. The goal of this work is to model rill formation risk along the Heritage Trail using a pre-processed LiDAR elevation dataset.

Rill formation can be understood as a function of surface characteristics, slope, and runoff rate (Yao et al., 2008). The surface of the trail, compacted Chapel Hill stone, is uniform throughout the study area. Slope along the trail can be measured with a number of basic methods, and can be adjusted by filling, terracing or other techniques. Runoff rate, in contrast, is a more complex variable. It is a function of the precipitation hyetograph as well as the contributing area and associated attributes such as infiltration rate, surface roughness, and storage (Laflen et al., 1997).

Rill formation along the Heritage Trail is one case of a widespread phenomenon: risks associated with storm water runoff. The approach taken here is to model rill formation risk along the trail as a function of contributing area. The LiDAR data is pre-processed and used as input for several flow routing algorithms. The results are compared to observed rill formation along the trail.

The importance of modeling storm water damage risk is in informing infrastructure design and maintenance decisions. Information regarding storm water risks is growing in relevance with continued development in South Carolina. Comparison of the outputs of several algorithms is done with the intent of identifying which algorithm will be most useful in localizing at-risk infrastructure. Infrastructure designers need methods to inform planning, implementation, and maintenance of robust storm water systems.

PROJECT DESCRIPTION

A LiDAR derived elevation dataset is used as input to flow direction and flow accumulation algorithms, producing estimates for contributing area to each 5x5 foot raster cell along the trail. The elevation values and horizontal resolution (cell width) of the dataset are in units of feet (0.3048 m). For simplicity and continuity, all linear measurements in this study are presented in terms of feet and inches.

The flow direction and flow accumulation algorithms vary in complexity. However, they are all basically
estimates of the area which contributes runoff to each cell of the dataset. Raster cells with high contributing area estimates are considered at risk for rill formation. Algorithm results are compared with actual rill formation along the trail by constructing ROC curves. The area under the ROC curve is a metric by which the performance of the different algorithms can be evaluated. A further processing step filters the results by selecting the maximum value within given radii. This filtering process can be used to estimate the appropriate resolution for interpreting the results.

METHODS

The LiDAR data used in this project was collected by Towill Inc. for the South Carolina Department of Natural Resources in 2011. The data was collected at a nominal pulse spacing of 1.4 meters. Following collection, the data was processed by Dewberry Geospatial Services Group using a variety of software suites. LiDAR point data were filtered and interpolated to create a seamless, hydro flattened raster dataset. The vertical accuracy was referenced against 78 National Geodetic Survey checkpoints, and the RMSE of the Pickens county portion of the dataset was determined to be 0.39 ft. The data and metadata were provided by Pickens County GIS Mapping.

Elevation Data Pre-Processing

The elevation data was cropped to the area of interest and adjusted to represent storm drains, berms, and stream channels. The area of interest includes all areas which contributed to runoff on the Heritage Trail. The storm drain adjustment was carried out by lowering cells which corresponded to underground storm drain vectors from the CU Atlas dataset. The CU Atlas dataset is a Computer Aided Drafting (CAD) .dwg file maintained by Clemson University surveyors. The cells were lowered by 3 feet. There were two areas where earthworks affecting surface flow had taken place since the LiDAR data was collected. Earthworks were located on the map and the elevation data was adjusted by raising corresponding cells by 2 feet. Finally, the stream channel, as determined by the D8 flow direction algorithm (discussed below), was lowered by 1 foot. The stream definition threshold was set at 19,000 cells (10.9 acres) based on observation of the landscape. An approximate estimation of stream definition threshold is sufficient for this study: the trail surface under consideration does not extend in to the stream bed. Although parts of the trail were flooded by the streams during the study period, the trail was not damaged by the flooding. The trail surface is not crossed by any flow with contributing area greater than 2 acres.

Figure 1: The Trail and Pre-Processed Features

After the aforementioned adjustments were made, remaining sinks were filled to create the pre-processed elevation dataset. Observation of filled sinks did not indicate that further pre-processing was necessary.

Trail and Rill Mapping

The Heritage Trail was mapped using GPS. The resulting GPS points were used to create lines and then buffered by 5 feet to create polygons. Photographs were taken every 10 feet along the trail when it was first opened so that observations of rill formation could be better qualified. The rills that formed were quite distinct, each being greater than 2 inches deep and 4 inches wide. They ranged in length from less than 3 feet to over 30 feet. They were input as line features across the trail polygon and subsequently buffered by 5 feet. The trail and rill polygons were then converted to raster format, corresponding with the elevation data.

Figure 1 shows elevation, infrastructure, berms, stream channels, the Heritage Trail, bridges, and rill observations. Bridges located along the trail correspond with the streams in the elevation data.

Flow Direction Algorithms

The ArcMap ‘Flow Direction’ tool, part of the Spatial Analyst extension, is an implementation of the D8 flow direction algorithm originally developed by Jenson and Domingue (1988). D8 type flow direction algorithms route flow from each cell to a single neighboring cell, typically the one with the greatest drop. The ArcMap implementation has several disadvantages: it approximates the square root of 2 as 1.5 to reduce processing time; and it is closed source and unavailable for public review – a black box. Furthermore, because flow is only routed to a single neighboring cell, D8 type algorithms fail to represent divergent flow patterns.

The D-infinity algorithm (Tarboton, 1997) is capable of routing flow from each cell to two neighboring cells,
proportioning flow according to geometric calculations of slope and angle across 8 facets. It is freely available for download and public scrutiny as part of the TauDEM software package (Tarboton, 2012).

Monte Carlo simulations have been used to model the propagation of stochastic error in elevation data to derivatives such as contributing area (Oksanen and Sarjakoski, 2005). Although the results are promising, Monte Carlo type algorithms require extensive computational processing, and implementation can be complex (Zandbergen, 2011). The basic premise is that an estimate of error in the elevation data is used to randomly adjust the data before deriving the output of interest. Repeated many times over, the simulated outputs are then aggregated with the expectation of finding some convergence on a stable result or set possible of results. A Monte Carlo technique was used to model uncertainty in the elevation data by creating 1,000 elevation simulations. The simulations were spatially auto-correlated error with a standard deviation equal to the measured Root Mean Square Error of the LiDAR dataset. The D8 and D-infinity ‘Flow Direction’ and ‘Flow Accumulation’ tools were then used on the simulated elevation datasets. Results were aggregated by calculating the mean contributing area value of each cell through the set of simulations.

The output rasters of the four algorithms were then filtered 4 times. Each filter created a new raster output by assigning a value to each cell according to the maximum value in the input raster within a specified radius of the cell. Maxima filters were applied at radii of 10, 20, 40, and 80 feet. This resulted in 20 output rasters of relative rill formation risk as a function of contributing area along the trail. These rasters were used to construct ROC curves by comparison with the trail and rill rasters previously developed.

The ROC curves plot the sensitivity (true positive/total positive) against the fallout (false positive/total negative) at each threshold of contributing area to illustrate the performance of the models as binary classifiers of rill formation (Hanley and McNeil, 1982). Better performance is indicated by greater area under the ROC curve. The area under the ROC curves for each contributing area algorithm has been calculated at different maxima filter radii.
As can be seen from figures 2 and 3 the algorithms performed fairly well in modeling rill formation risk along the trail as a function of contributing area. Figure 2 shows a cartographic depiction of the trail with the model outputs overlaid. Figure 3 shows the ROC curve of the model outputs when filtered with a kernel radius of 2 cell widths. The performance of the models can be evaluated by comparing the curves to a straight diagonal line of slope equal to 1. Greater area between the curve and the diagonal means better model performance.

Table 1 shows the performance of the algorithms with different filter radii in terms of the Area Under the Curve (AUC) of the ROC. An AUC of 1 would indicate that an algorithm could be perfectly calibrated to the input elevation and rill datasets. The Monte Carlo algorithms generally outperformed the others, performing well at a filter radius of 10 feet, indicating that stochastic simulation may be a more robust approach. The D-infinity algorithm generally outperformed the D8 algorithm.

DISCUSSION

Although the Monte Carlo approach may be more robust, when considering additional factors such as implementation and processing time, simply using the D-infinity algorithm may be more suitable for practical applications.

If these results can be generalized to other landscapes and other forms of storm water damage, then it will be possible to create detailed and accurate models of storm water runoff using LiDAR elevation data in conjunction with other high resolution datasets. Location and sizing of various best management and low impact development practices can be facilitated by methods such as described in this work. In fact, an addition to the Heritage Trail is under construction, and the D-infinity algorithm has been used to design diversion channels to prevent storm water damage in the future.

LITERATURE CITED


