The Effect of DEM Resolution on the Computation of Hydrologically Significant Topographic Attributes

by

David Alexander Crosby

A thesis submitted in partial fulfillment of the requirements for the degree of
Master of Arts
Department of Geography
College of Arts and Sciences
University of South Florida

Major Professor:  Paul Zandbergen, Ph.D.
Robert Brinkmann, Ph.D.
Mark Ross, Ph.D.

Date of Approval:
April 6, 2006

Keywords:  GIS, LIDAR, DEM, terrain analysis, geomorphometry

© Copyright 2006, David Alexander Crosby
Dedication

This thesis is dedicated to my family
Acknowledgements

I would like to acknowledge and sincerely thank all of the individuals who have helped me during the research and writing of this thesis. First, I would like to thank Paul Zandbergen for his guidance, ideas, and expertise. Thank you for the countless hours you spent working through techniques and theory with me and helping make the final product as solid as possible. I would also like to thank my committee members, Robert Brinkmann and Mark Ross for their numerous suggestions and critiques. I truly appreciated working with all of you.

I would like to sincerely thank my family for their encouragement during my graduate study. I would also like to thank Paul Zandbergen, Martin Bosman, Steven Reader, Jayajit Chakraborty, and Philip Reeder for helping to provide me with much of the background knowledge and expertise needed to accomplish this research. Thanks as well to my early professors at the University of Toronto for stimulating and piquing my interest in geography and GIS.
Table of Contents

List of Tables iii

List of Figures iv

Abstract vi

Chapter One: Introduction 1
  1.1 Background 1
  1.2 Goal 4
  1.3 Objectives 5
  1.4 Description of Study Area 6

Chapter Two: Literature Review 9
  2.1 Topographic Models 9
  2.2 Creating Terrain Models through Interpolation 11
  2.3 LIDAR 12
  2.4 Topographic Attributes 17
    2.4.1 Primary Topographic Attributes 18
    2.4.2 Secondary Topographic Attributes 19
  2.5 Detailed Description of Attributes of Interest 22
    2.5.1 Slope 22
    2.5.2 Curvature 22
    2.5.3 Upslope Contributing Area and Specific Catchment Area 23
    2.5.4 Topographic Wetness Index 24
    2.5.5 Stream Power Index 25
  2.6 Hydrologic Modeling and Hydrologically Conditioned DEMs 25
  2.7 Flow Routing Algorithms 27
  2.8 TOPMODEL 28
  2.9 DEM Resolution 31
  2.10 Channel Network Characteristics 32
  2.11 Extraction of a Stream Network from a DEM 35
  2.12 Threshold for the Extraction of Stream Networks 36

Chapter Three: Methodology 39
  3.1 Methodology Overview 39
  3.2 Data Sources 40
  3.3 Processing 41
    3.3.1 Resampling Original DEM 41
List of Tables

Table 1: Primary Topographic Attributes that can be computed by Terrain Analysis from DEM Data, from Wilson and Gallant, 2000 18
Table 2: Secondary Topographic Attributes that can be computed by Terrain Analysis from DEM Data, from Wilson and Gallant, 2000 20
Table 3: Number of cells to initiate a stream network 46
Table 4: Summary statistics for elevation 57
Table 5: Results of the Kolmogorov-Smirnov Test on Elevation 59
Table 6: Summary statistics for slope 62
Table 7: Results of the Kolmogorov-Smirnov Test on Slope 64
Table 8: Summary statistics for curvature 67
Table 9: Results of the Kolmogorov-Smirnov Test on the Curvature 69
Table 10: Summary statistics for plan curvature 71
Table 11: Results of the Kolmogorov-Smirnov Test on the Plan Curvature 73
Table 12: Summary statistics for profile curvature 75
Table 13: Results of the Kolmogorov-Smirnov Test on the Profile Curvature 77
Table 14: Summary statistics for stream power index 79
Table 15: Results of the Kolmogorov-Smirnov Test on the Stream Power Index 82
Table 16: Summary statistics for wetness index 84
Table 17: Results of the Kolmogorov-Smirnov Test on the Wetness Index 86
Table 18: Cell Agreement Count Matrix for Boolean Stream Network 101
Table 19: Cell Agreement Count Matrix for 20' DEM Derived vs. Mapped Stream Network 102
Table 20: Kappa Index of Agreement for 20 foot DEM 104
Table 21: Results of Intersection of Mapped Stream Buffer and Derived Stream Networks 105
Table 22: Count of Stream Segments by Order 109
Table 23: Bifurcation Ratios 110
Table 24: Length of Streams by Order (in feet) 110
Table 25: Stream Length Ratios 111
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1</td>
<td>Study Watershed Showing Topographic Relief</td>
<td>7</td>
</tr>
<tr>
<td>Figure 2</td>
<td>Study Site in North Carolina</td>
<td>8</td>
</tr>
<tr>
<td>Figure 3</td>
<td>LIDAR Data Acquisition, from NC Floodmaps Fact Sheet, 2003</td>
<td>15</td>
</tr>
<tr>
<td>Figure 4</td>
<td>Fourth order polynomial in curvature calculation, from ArcGIS Documentation (ESRI, 2005)</td>
<td>23</td>
</tr>
<tr>
<td>Figure 5</td>
<td>Strahler Stream Ordering</td>
<td>34</td>
</tr>
<tr>
<td>Figure 6</td>
<td>Image shows road bank impeding derived streamflow</td>
<td>44</td>
</tr>
<tr>
<td>Figure 7</td>
<td>Profile Transect Location in Watershed</td>
<td>54</td>
</tr>
<tr>
<td>Figure 8</td>
<td>Elevation Variability along a Transect at Different Cell Sizes</td>
<td>56</td>
</tr>
<tr>
<td>Figure 9</td>
<td>Minimum and Maximum Computed Elevation by Cell Size</td>
<td>58</td>
</tr>
<tr>
<td>Figure 10</td>
<td>CFD for Elevation</td>
<td>59</td>
</tr>
<tr>
<td>Figure 11</td>
<td>Slope Variability along a Transect at Different Cell Sizes</td>
<td>61</td>
</tr>
<tr>
<td>Figure 12</td>
<td>Maximum and Mean Computed Slope by Cell Size</td>
<td>62</td>
</tr>
<tr>
<td>Figure 13</td>
<td>Mean Computed Slope by Cell Size with Log Trend Line</td>
<td>63</td>
</tr>
<tr>
<td>Figure 14</td>
<td>CFD for Slope</td>
<td>64</td>
</tr>
<tr>
<td>Figure 15</td>
<td>Curvature Variability along a Transect at Different Cell Sizes</td>
<td>66</td>
</tr>
<tr>
<td>Figure 16</td>
<td>Maximum and Minimum Computed Curvature by Cell Size</td>
<td>67</td>
</tr>
<tr>
<td>Figure 17</td>
<td>CFD for Curvature</td>
<td>68</td>
</tr>
<tr>
<td>Figure 18</td>
<td>Plan Curvature Variability along a Transect at Different Cell Sizes</td>
<td>70</td>
</tr>
<tr>
<td>Figure 19</td>
<td>Maximum and Minimum Computed Plan Curvature by Cell Size</td>
<td>71</td>
</tr>
<tr>
<td>Figure 20</td>
<td>CFD for Plan Curvature</td>
<td>72</td>
</tr>
<tr>
<td>Figure 21</td>
<td>Profile Curvature Variability along a Transect at Different Cell Sizes</td>
<td>74</td>
</tr>
<tr>
<td>Figure 22</td>
<td>Maximum and Minimum Computed Profile Curvature by Cell Size</td>
<td>75</td>
</tr>
<tr>
<td>Figure 23</td>
<td>CFD for Profile Curvature</td>
<td>76</td>
</tr>
<tr>
<td>Figure 24</td>
<td>Stream Power Index Variability along a Transect at Different Cell Sizes</td>
<td>78</td>
</tr>
<tr>
<td>Figure 25</td>
<td>Mean Computed Stream Power Index by Cell Size</td>
<td>80</td>
</tr>
<tr>
<td>Figure 26</td>
<td>CFD for Plan Stream Power Index</td>
<td>81</td>
</tr>
<tr>
<td>Figure 27</td>
<td>Wetness Index Variability along a Transect at Different Cell Sizes</td>
<td>83</td>
</tr>
<tr>
<td>Figure 28</td>
<td>Maximum, Minimum, and Mean Computed Wetness Index by Cell Size</td>
<td>84</td>
</tr>
<tr>
<td>Figure 29</td>
<td>Mean Computed Wetness Index by Cell Size with Log Trend Line</td>
<td>85</td>
</tr>
<tr>
<td>Figure 30</td>
<td>CFD for Wetness Index</td>
<td>86</td>
</tr>
<tr>
<td>Figure 31</td>
<td>Orthophoto Derived Stream Network</td>
<td>88</td>
</tr>
<tr>
<td>Figure 32</td>
<td>Streams Derived from 20 foot DEM</td>
<td>89</td>
</tr>
<tr>
<td>Figure 33</td>
<td>Streams Derived from 40 foot DEM</td>
<td>90</td>
</tr>
</tbody>
</table>
Figure 34: Streams Derived from 80 foot DEM 91
Figure 35: Streams Derived from 160 foot DEM 92
Figure 36: Streams Derived from 320 foot DEM 93
Figure 37: Streams Derived from a 20 foot Cell Size and Photogrammetrically Mapped Streams 94
Figure 38: Streams Derived from a 40 foot Cell Size and Photogrammetrically Mapped Streams 95
Figure 39: Streams Derived from a 80 foot Cell Size and Photogrammetrically Mapped Streams 96
Figure 40: Streams Derived from a 160 foot Cell Size and Photogrammetrically Mapped Streams 97
Figure 41: Streams Derived from a 320 foot Cell Size and Photogrammetrically Mapped Streams 99
Figure 42: All Streams Derived from a DEM and Photogrammetrically Mapped Streams 100
Figure 43: Result of Error in Initiating a First-Order Stream, Cascade Effect 103
The Effect of DEM Resolution on the Computation of Hydrologically Significant Topographic Attributes

David Alexander Crosby

ABSTRACT

Terrain attributes computed from Digital Elevation Models (DEMs) are widely used in hydrology and hydrologic modeling. It is important to consider that the values of the attributes can be different depending on the resolution of the DEM from which they are derived. The question arises as to how much exactly the high-resolution DEMs created through LIDAR remote sensing techniques change the values of the terrain attributes when compared to lower resolution DEMs.

In this thesis a LIDAR-derived DEM of 20 feet resolution was resampled using a nearest-neighbour algorithm to various coarser resolutions to examine and quantify the effect of DEM resolution upon a series of hydrologically significant terrain attributes including slope, surface curvature, topographic wetness index, stream power index and stream networks. Values for slope and surface curvature are found to be smaller when computed from lower resolution DEMs; values for the topographic wetness index and stream power index are found to increase as DEM cell size increases.

The derived stream networks for each resolution were compared in terms of length per stream order, drainage density, bifurcation ratio, and overall accuracy.
indicating a loss of small detail, but only a modest change in the overall stream network morphometry. This research suggests that it is possible to establish relationships that quantify the effects of DEM resolution upon hydrologically significant terrain attributes, which can then be considered when processing DEMs from various resolutions for the purpose of parameterizing hydrologic models.
Chapter 1

Introduction

1.1 Background

Terrain plays a fundamental role in modulating earth surface and atmospheric processes. Terrain is so fundamental to these processes that an understanding of the nature of terrain can also give understanding of the nature of these processes, in both analytical and subjective terms (Hutchinson and Gallant, 2000). Knowledge of terrain is important and fundamental to many applications and disciplines, including hydrology, geomorphology, ecology and biology (Wilson and Gallant, 2000). Terrain can be thought of as the base upon which all surficial earth processes occur. The following illustrates the linkage between terrain and surficial earth processes.

Surface morphology has an impact both on catchment hydrology and terrain derivatives, such as slope and aspect, and has a direct impact on solar shading and surface insolation (Wilson and Gallant, 2000). The shape of the land surface affects the movement and storage of water, nutrients, and other sediment on the landscape. The movement of water and deposition of material in turn has implications for soil development and geomorphology. Further, this distribution of moisture, nutrients, heat, and solar radiation has a direct effect upon photosynthesizing plants (Wilson and Gallant, 2000). Terrain models generated from elevation data, terrain analysis techniques, and
Geographic Information Systems (GIS) are tools that allow the informed linkage between surface morphology and biophysical processes. With the advent of new, higher resolution elevation data from new collection methods and sensors comes more opportunity to explore there processes at scales not previously explored.

Beven and Moore (1992) noted that digital terrain modeling is not new in the field of hydrology, and in fact the characterization of the topography must be important in hydrology. However, what is different now is that the era of GIS, simulation visualization software, and workstation computing power has arrived and is rapidly maturing. Further, the quantity of high resolution digital elevation data has expanded dramatically and the revolutionary aspects of the work described in their edited volume result from a revolution in the information available, rather than from radical changes in methodology.

The quantity and quality of digital elevation data has continued to expand, and with the emergence of fine spatial resolution data from sources such as Light Detection and Ranging (LIDAR) sensors, new opportunities for physical-based modeling have been opened up (Atkinson, 2002). Though data quality may be higher, it is difficult to determine a priori what level of accuracy is necessary for a given application. LIDAR data represents elevation at a fine spatial resolution, but it remains to be seen whether this finer resolution is able to better represent terrain attributes, and lend better information to the study of hydrology and the predictions generated by hydrologic models.

The importance of elevation data to hydrology has been clearly articulated in the literature. For example:
"Examination of hydrologic processes also requires other information about the surface and subsurface of the earth. Among these, perhaps the most important is topography. Elevation and related parameters (slope, aspect, and drainage area) exert an important control on surface and subsurface hydrology and ecosystems. Topography influences intercepted radiation, precipitation and runoff movement of sediment, evaporation, soil moisture, and vegetation characteristics" (National Research Council, 1991).

Terrain analysis work is most often conducted from within a GIS. GIS is sometimes defined as an arrangement of computer hardware, software, and geographic data that people interact with to integrate, analyze, and visualize the data; identify relationships, patterns, and trends; and find solutions to problems. Aronoff (1989) defines it simply as a computer-based system used to store and manipulate geographic information. Longley, et al. (2001) provides an excellent summary of the origins of GIS, as well as an explanation of its applicability to different disciplines. As technology has changed over the years, the range of geoprocessing and analytical tools available within a GIS has grown exponentially (Goodchild, 2004). Longley, et al. (2001) has extended the definition to explain that a GIS is a system capable of performing any conceivable operation on data obtained from maps. A survey of definitions in the literature, in fact, reveals that data are always mentioned as a central part of the definition. GIS has transformed the way spatial data is analyzed, stored, and manipulated, and encouraged the proliferation of research into data manipulation and processing.
The relationship between data and GIS tools is mutually beneficial. It is the increased availability of high-resolution, continuous digital elevation data as well as new computerized terrain analysis tools that increased the popularity of research at what Wilson and Gallant (2000) term the *toposcale*. It is the influence of surface morphology at the toposcale that controls catchment hydrology, as well as slope, aspect, and other terrain derivatives.

The application that this thesis is concerned with are the hydrologically significant topographic attributes obtained from digital elevation data, including the accuracy and density of stream networks derived from digital elevation data. Scale in the context of GIS and terrain analysis can be though of as a window of perception or a measuring tool through which a landscape can be viewed or perceived (Levin cited in Marceau and Hay, 1999). Changing the scale can change the patterns of reality, which has implications for understanding spatial relationships, and modeling natural systems including a terrain surface (Marceau and Hay, 1999). The specific point of inquiry relevant to this research concerns the effect of DEM scale and grid resolution upon hydrologically related terrain derivatives and stream networks. What can we gain, if anything from the proliferation of high-resolution digital elevation data acquisition that is poised to take place with the advent of new data collection methods?

1.2 Goal

To determine the effects of DEM resolution upon hydrologically significant terrain attributes, including stream networks.
1.3 Objectives

Objective One: To determine the effects of DEM resolution on hydrologically significant terrain derivatives including slope, plan curvature, profile curvature, overall curvature, topographic wetness index, and stream power index.

Hypothesis: 

- **Slope:** As DEM cell size increases, derived slope values will decrease, and the mean slope in a watershed will decrease.

- **Plan, profile, and overall curvature:** As DEM cell size increases, the range of values for the curvature parameters will become limited, and mean values of the curvature parameters in the watershed will decrease.

- **Topographic Wetness Index:** As DEM cell size increases, watersheds will be modeled to be “wetter”, and the mean of the topographic index will increase as cell size does. Higher values of the wetness index will be computed, and low values will be less likely.

- **Stream Power Index:** As DEM cell size increases, mean stream power index values will increase, as specific catchment areas will be larger, and the stream power index will increase proportionally to them.

These terrain attributes are chosen as they are important to the study of hydrology and to hydrologic modeling. These attributes of a surface have the ability to influence surficial processes such as flow acceleration and deceleration, flow convergence and divergence, soil erosion and deposition, and soil saturation.

Objective Two: To determine how the resolution of a DEM affects the morphology and accuracy of the streams derived from it.

Hypothesis: 

- **Stream Length:** As DEM cell size increases, the drainage density of streams derived from the DEM will decrease, as stream lengths will decrease when derived from increasingly coarse DEMs due to lack of detail.

- **Bifurcation Ratio:** As DEM cell size increases, the bifurcation ratio between one order of stream and the next will remain constant with no clear increase or decrease, although the values will become less reliable.
Stream Accuracy. As DEM cell size increases, the accuracy of stream locations derived from it will decrease, as compared to streams mapped through orthophotography.

The ability to understand the hydrologic properties of a watershed is a central component of understanding and predicting hydrologic response within a watershed. Stream morphology affects the watershed response of many hydrologic processes including precipitation events, and the erosion, deposition, and movement of sediment. These particular stream morphological attributes were chosen because of their importance to the study of hydrology and hydrologic modeling.

1.4 Description of Study Area

The study area is a small watershed in the southeast corner of Wake County North Carolina as shown in Figures 1 and 2. Located in the Piedmont area of the state, the climate is extremely variable due to the influence of the topographic variety to the west, and the Gulf Stream on the coast. The area is dominated by sandy loam well drained soils. Relief in the area is moderate, with elevation ranging between 173 feet and 518 feet above sea level, with slopes generally between 2 and 6 percent. Hydrologic characteristics include lakes of various sizes, and a well defined dendritic stream network. The area is generally an erosional environment, and the watershed is approximately 68 square miles in size.

This area was chosen for a number of reasons. The North Carolina Floodplain Mapping program collects and compiles high-quality LIDAR DEM data for many of the areas of the state. Freely available LIDAR data for this area was available already in DEM format. This particular area has additional benefits including a natural topography
of moderate relief making any effects of DEM resolution observable, and the size of the area is large enough to produce statistically significant results and have streams of a sufficient number of orders to make meaningful comparisons. A very large scale photogrammetrically mapped stream network is available for this area from Wake County government. This stream network will enable meaningful comparisons between DEM derived stream networks and photogrammetrically mapped ones.

Figure 1: Study Watershed Showing Topographic Relief
Figure 2: Study Site in North Carolina
Chapter 2

Literature Review

2.1 Topographic Models

Moore et al. (1991) describe a Digital Elevation Model (DEM) as an ordered array of numbers that represent the spatial distribution of elevations above some arbitrary datum in the landscape. Traditionally, this data would be captured through photogrammetric techniques. Softcopy or hardcopy stereoplotters would be used with either aerial photographs or satellite imagery to interpret and capture elevation information (Carter, 1988). As this type of equipment is not readily available to many potential consumers of DEMs, elevation information is often digitized or captured directly through electronic means, from topographic maps displaying elevation contour information. Maps of this nature are created and are available from the United States Geological Survey (USGS) and others (Moore, et al., 1991). Irrespective of how the source elevation data is captured when creating a DEM, there are a number of different DEM surface representation structures. Each has different qualities, and the data structure chosen will depend on the end application of the DEM. A structure chosen for computing water storage volumes will differ from one chosen for computing the topographic attributes of a landscape (Moore, et al., 1991, Schneider, 2001).
It is generally accepted that there are three different ways of structuring digital elevation data. These include regular square-grid raster representations, triangulated irregular networks (TINs), and contours of equal elevation (Wilson and Gallant, 2000).

Square-grid DEMs are the most widely used data structure. They have several advantages, including their simplicity (single elevation value stored for each independent grid cell), ease of computer implementation, and computational efficiency (Moore et al., 1991, Aronoff 1989, Wilson and Gallant 2000). There are disadvantages as well. First, although there are compression methods available, the size of the grid mesh will often affect the storage requirements, computational efficiency, and the quality of the results (Moore et al., 1991). Further, square grids cannot easily handle abrupt changes in topography and computed upslope flow paths will tend to zigzag across the landscape, making them unrealistic (Moore et al., 1991).

Triangulated irregular networks (TINs) are the second data structure. A TIN is composed of nodes, edges, triangles (facets), and hull polygons. These facets consist of planes joining the three adjacent points in the network and are constructed in such a way that they meet the Delauney criterion, which ensures that no vertex lies within the interior of a circle constructed around the triangles in the network (Wilson and Gallant, 2000).

TINs sample surface-specific points, such as peaks, ridges, and breaks in slope, and form an irregular network of points stored as a set of $x$, $y$, and $z$ values together with pointers to their neighbours in the net (Moore et al., 1991). TINs are advantageous in that they can easily incorporate discontinuities and may constitute efficient data structures because the density of the triangles can be varied to match the roughness of the terrain, thus making them flexible and efficient (Moore et al., 1991). Grid-based DEMs
do not have this flexibility ability to locally adjust the grid size to the dimensions of topographic land surface features (Garbrecht and Martz, 2000).

Contour-based networks consist of isolines representing lines of equal elevation on the surface. These lines are stored as x, y coordinate pairs of points located along these lines (Moore, et al., 1991). Contours allow a landscape to be readily visualized, as the isolines are closer together in areas of steep topography, and further apart in areas with less relief.

Topographic attributes such as slope, aspect, plan curvature, profile curvature, and the specific catchment area can be derived from grid-based DEMs, TINs, and contours. However, this is done much more efficiently when using the grid-based data structure (Moore, et al., 1991). Details regarding terrain attributes and their determination will be discussed later. The rest of this thesis will focus on the more popular and suitable grid based Digital Elevation Model, hereinafter referred to simply as ‘DEM’.

2.2 Creating Terrain Models through Interpolation

A DEM is often interpolated from point and/or line sample data which has a known or estimated elevation value (Kienzle, 2004). There are many mathematical functions that can be used to fit a smooth surface through a set of sample of points with elevations. More popular ones include local and global polynomial trend surfaces, inverse-distance weighted (IDW) interpolation, splining, and kriging. All of these are implemented in popular commercial GIS software applications such as ArcGIS® (ESRI, 2005) and selectively in standalone analysis packages such as the Terrain Analysis System (TAS) (Lindsay, 2005). Depending on the implementation, each one of these
interpolation functions have a set of parameters that need to be specified, and the results of the interpolation can vary significantly from one another (Kienzle, 2004). Analysis of the root mean square (RMS) error, an indicator of the accuracy of the interpolated surface, can be large and will differ between interpolation functions (Kienzle, 2004).

One algorithm not particularly suitable for DEM interpolation from irregularly spaced elevation points (i.e. most sample elevation data sets) is the IDW method. This method tends to create unrealistically shaped terrain features, often referred to as “Bull’s Eyes” (Kienzle, 2004). The interpolation algorithms that offer the best results include the regular spline with tension and ANUDEM (Huchinson, 1989). ANUDEM is based on a thin-plate spline technique, but has added features that contribute to its creation of DEMs with accurate representation of terrain, and suitability for hydrologic modeling.

2.3 LIDAR

LIDAR is an acronym for Light Detection and Ranging. This technology can be used to determine distance, determine chemical composition of the atmosphere, or for determining the velocity of a moving object. LIDAR operates in much the same way as traditional RADAR, but instead of emitting radio energy and awaiting a reflective response, the LIDAR sensor emits short bursts of laser light towards an object or a surface. As the emitted light interacts with objects and surfaces during its travel, it is reflected back towards the sensor. The time it takes for the light to be reflected back to the sensor reveals the distance of the object or surface from the sensor. The intensity of the return is also measured. The distance from the light emitting sensor to the object being detected is determined from mathematical equations using the speed of light.
LIDAR sensors can be ground based (known as Terrestrial Laser Scanning or TLS), airborne (known as Airborne Laser Scanning or ALS), or spaceborne.

Airborne LIDAR sensors emit between 5,000 and 50,000 laser pulses per second in a scanning array. Figure 3 shows the most popular scanner configuration, which moves back and forth sideways relative to the points measured on the ground. The average point spacing in the cross-flight direction is determined by the scan angle and flying altitude. Further, both flying height and airspeed determine the average point spacing in the in-flight direction. Conceptually, each laser pulse can be thought of as a cylinder of light which has a diameter and length, as each laser pulse has a number of properties, including the pulse width which is typically between 0.5 and 1 meter in diameter, and a pulse length. The pulse length refers to the length of time lapse between the time the laser pulse was turned on and off. The three basic types of LIDAR sensing include Differential Absorption LIDAR (DIAL), Doppler LIDAR, and range finding.

DIAL LIDAR is used to measure the chemical composition and concentration of molecules in the atmosphere. In order to do this the LIDAR sensor must emit two different wavelengths of light so that one wavelength can be partially absorbed by the chemical in the atmosphere and one wavelength can be reflected back to the sensor. Once the light is reflected back, the chemical concentration can be determined by measuring the difference in the properties of the two light wavelengths (Kavaya, 1999).

Doppler LIDAR is used to determine the velocity of a moving object or target. Targets can be either hard or an atmospheric target as small as dust particles. By measuring the velocity of dust particles, scientists are essentially measuring atmospheric wind speed. This information can be used for future weather predictions as well as
studying current extreme weather or weather anomalies. Doppler LIDAR works by measuring the Doppler shift of the object or dust particles. When the light is reflected back to the sensor, the wavelength is either shorter or longer depending on whether the object or dust particle is moving towards or away from the sensor, respectively (Kavaya, 1999).

Range finding LIDAR is the most basic kind of LIDAR and is the type used to determine terrain elevations. It operates as described earlier, by emitting laser light, and measuring the return time and intensity of the pulse. There are 3 components to collecting range finding LIDAR data to produce a DEM. First, one needs the LIDAR sensor itself. This will transmit the laser pulses and record the distance information from the reflected light. Second, the aircraft needs to have a differential Global Positioning System (GPS) on board. The GPS on board records the location of the sensor in 3 dimensions, including the altitude (z), latitude (y), longitude (x). Locations are recorded continuously at every point while scanning with the LIDAR sensor relative to a GPS base station, or can be corrected post-mission based on observations of a GPS base station located near the study area (NC Floodmaps, 2003). The third component is referred to as the Inertial Measuring Unit (IMU). The IMU is responsible for establishing and recording the pitch, yaw, and roll of the sensor, effectively measuring the orientation of the sensor about the three dimensions noted earlier (NC Floodmaps, 2003). In effect, the GPS records the location of the aircraft in three dimensions, and the IMU records in which direction the sensor is oriented. When all of this information is processed, an accurate location can be specified for every return received by the LIDAR sensor.
LIDAR sensors are capable of receiving multiple returns, some up to five returns per pulse. This means that a 30-KHz sensor (30,000 pulses per second) must be capable of recording up to 150,000 returns per second. The "first return" recorded by a LIDAR sensor is the first object hit by a laser pulse. This could be a treetop, rooftop, ground point, or even a suspended object such as a bird in flight or a power transmission line. When a laser pulse hits a soft target (i.e., a forest canopy), the first return represents the top of that feature. However, a portion of the laser light beam might continue downward below the soft target and hit a tree branch. This would provide a second return, although multiple returns are possible. Theoretically, the last return represents the bare earth.
surface, but this is sometimes not the case. On occasion, and in some locations, vegetation is so thick that no portion of the laser pulse can penetrate to the ground. This could be the case with sawgrass, mangrove, and dense forests where a person on the ground cannot see the sky through the canopy (NC Floodmaps, 2003).

As LIDAR sensors record multiple returns from each beam of light emitted from the sensor, these multiple returns can be useful for differentiating and characterizing terrain, buildings, and even tree canopies. While the first and the last are often the returns of greatest interest, there is ongoing work to determine the utility of the intermediate returns occurring between the first and last returns.

The accuracy of each LIDAR data point depends on many factors including the flight altitude, the precision of the positioning instruments (the GPS and IMU), and the amount and quality of ground control applied. The resolution of the dataset and accuracy of applications built using the dataset depend on this accuracy as well as on the density of points within the surveyed area. In general terms, the accuracy and density of individual return points increase as the altitude of the flight and its speed is decreased. Increasing or decreasing the pulse rate of the laser can also affect the point density, or post spacing (Plaster, 2002). The quality of the information resulting from LIDAR data collection is also dependent on the algorithms that are used to filter out vegetation and other ancillary information. Care must be taken when filtering out the data for the last return (terrain) bare earth surface. Each LIDAR data vendor has a proprietary algorithm to do this, and refining and optimizing this methodology is an ongoing area of research.
2.4 Topographic Attributes

Most of the common topographic attributes such as slope, aspect, plan and profile curvature, and specific catchment area can be derived from elevation data represented as a DEM, TIN, or contours for each and every element as a function of its surroundings (Moore et al., 1991). Individual terrain analysis tools have been classified in various ways based on the characteristics of the computed attributes and/or their spatial extent. Some distinguish tools that perform operations on “local” neighbourhoods from those that perform operations on extended or global neighbourhoods (calculation of upslope drainage areas, etc.) (Burrough and McDonnell, 1998). Primary attributes that are computed directly from the DEM are usually distinguished from secondary or compound attributes that involve combinations of primary attributes. These usually constitute physically based or empirically derived indices that can characterize the spatial variability of specific processes occurring in the landscape (Moore et al., 1991). This same logic is adopted here. Primary attributes include slope, aspect, plan and profile curvature, flow-path length, and upslope contributing area. Most of these topographic attributes are calculated from the directional derivatives of a topographic surface. They can be computed directly with a second-order finite difference scheme or by fitting a bivariate interpolation function $z = f(x, y)$ to the DEM and then calculating the derivatives of the function (Wilson and Gallant, 2000). In many cases, it may be preferable to calculate a depressionless (hydrologically corrected) DEM first; specifying one or more rules to determine drainage directions and the connectivity of individual elements in order to calculate flow path lengths and upslope contributing area. The overall aim is to be able to use the computed attributes to describe the structure, form, catchment position,
and surface attributes of hillslopes and stream channels comprising drainage basins. Many researchers, including Band (1986), and Jenson and Domingue (1988), have used computed topographic attributes to generate formal landform classifications (Wilson and Gallant, 2000).

The secondary or compound attributes that are computed from two or more primary attributes are important because they offer an opportunity to describe pattern as a function of process. Those attributes that quantify the role played by topography in redistributing water in the landscape and in modifying the amount of solar radiation received at the surface have important hydrological, geomorphological, and ecological consequences in many landscapes. These attributes may affect soil characteristics, as soil is affected by the way water moves through the environment in many landscapes, the distribution and abundance of soil water, the susceptibility of landscapes to erosion by water, and the distribution and abundance of flora and fauna (Wilson and Gallant, 2000).

### 2.4.1 Primary Topographic Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Definition</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Altitude</td>
<td>Elevation</td>
<td>Climate, vegetation, potential energy</td>
</tr>
<tr>
<td>Upslope height</td>
<td>Mean height of upslope area</td>
<td>Potential energy</td>
</tr>
<tr>
<td>Aspect</td>
<td>Slope azimuth</td>
<td>Solar insolation, evapotranspiration, flora and fauna</td>
</tr>
<tr>
<td></td>
<td></td>
<td>distribution and abundance</td>
</tr>
<tr>
<td>Slope</td>
<td>Gradient</td>
<td>Overland and subsurface flow velocity and runoff rate, precipitation, vegetation, geomorphology, soil water content, land capability class</td>
</tr>
<tr>
<td>Upslope slope</td>
<td>Mean slope of upslope area</td>
<td>Runoff velocity</td>
</tr>
<tr>
<td>Dispersal</td>
<td>Mean slope of dispersal</td>
<td>Rate of soil drainage</td>
</tr>
<tr>
<td>slope</td>
<td>area</td>
<td>Time of concentration</td>
</tr>
<tr>
<td>---------------</td>
<td>----------------------------------------------------------------------</td>
<td>----------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Catchment slope</td>
<td>Average slope over the catchment</td>
<td></td>
</tr>
<tr>
<td>Upslope area</td>
<td>Catchment area above a short length of contour</td>
<td>Runoff volume, steady-state runoff rate</td>
</tr>
<tr>
<td>Catchment area</td>
<td>Area draining to catchment outlet</td>
<td>Runoff volume</td>
</tr>
<tr>
<td>Specific catchment area</td>
<td>Upslope area per unit width of contour</td>
<td>Runoff volume, steady-state runoff rate, soil characteristics, soil water content, geomorphology</td>
</tr>
<tr>
<td>Flow path length</td>
<td>Maximum distance of water flow to a point in the catchment</td>
<td>Erosion rates, sediment yield, time of concentration</td>
</tr>
<tr>
<td>Upslope length</td>
<td>Mean length of flow paths to a point in the catchment</td>
<td>Flow acceleration, erosion rates</td>
</tr>
<tr>
<td>Dispersal length</td>
<td>Distance from a point in the catchment to the outlet</td>
<td>Impedance of soil drainage</td>
</tr>
<tr>
<td>Catchment length</td>
<td>Distance from highest point to outlet</td>
<td>Overland flow attenuation</td>
</tr>
<tr>
<td>Profile curvature</td>
<td>Slope profile curvature</td>
<td>Flow acceleration, erosion/deposition rate, geomorphology</td>
</tr>
<tr>
<td>Plan curvature</td>
<td>Contour curvature</td>
<td>Converging/diverging flow, soil water content, soil characteristics</td>
</tr>
<tr>
<td>Tangential curvature</td>
<td>Plan curvature multiplied by slope</td>
<td>Provides alternative measure of local flow convergence and divergence</td>
</tr>
<tr>
<td>Elevation percentile</td>
<td>Proportion of cells in a user-defined circle lower than the center cell</td>
<td>Relative landscape position, flora and fauna distribution and abundance</td>
</tr>
</tbody>
</table>

### 2.4.2 Secondary Topographic Attributes

A number of the terms which are used in the secondary topographic attribute formulas warrant explanation. \( A_s \) is the specific catchment area in units of \((m^2 \ m^{-1})\). The specific catchment area is defined as the surface area contributing flow across a width of contour. \( T \) is the soil transmissivity when the soil profile is saturated. \( \beta \) is the local slope gradient, measured in degrees. \( A_e \) is the effective specific catchment area. \( A_e \) differs from \( A_s \) in that instead of representing all of the area that could be expected to contribute
to runoff as $A_s$ does, $A_e$ removes areas of natural storage such as lakes or marsh areas that would only contribute to runoff during a more significant (1 or 2 year) precipitation event.

Table 2: Secondary Topographic Attributes that can be computed by Terrain Analysis from DEM Data, from Wilson and Gallant, 2000

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Definition</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topographic wetness index</td>
<td>$W_T = \ln \left( \frac{A_s}{T \tan \beta} \right)$</td>
<td>This equation assumes steady state conditions and describes the spatial distribution and extent of zones of saturation (i.e., variable source areas) for runoff generation as a function of upslope contributing area, soil transmissivity, and slope gradient.</td>
</tr>
<tr>
<td></td>
<td>$W = \ln \left( \frac{A_s}{\tan \beta} \right)$</td>
<td>This particular equation assumes steady state conditions and uniform soil properties (i.e., transmissivity is constant throughout the catchment and equal to unity). This pair of equations predicts zones of saturation where $A_s$ is large (typically in converging segments of landscapes), $\beta$ is small (at base of concave slopes where slope gradient is reduced), and $T$ is small (on shallow soils). These conditions are usually encountered along drainage paths and in zones of water concentration in landscapes.</td>
</tr>
<tr>
<td></td>
<td>$W = \ln \left( \frac{A_e}{\tan \beta} \right)$</td>
<td>This quasi-dynamic index substitutes effective drainage area for upslope contributing area and thereby overcomes</td>
</tr>
</tbody>
</table>
| Stream-power indices | SPI = \( A_s \tan \beta \) | Measure of erosive power of flowing water based on assumption that discharge \( (q) \) is proportional to specific catchment area \( (A_s) \). Predicts net erosion in areas of profile convexity and tangential concavity (flow acceleration and convergence zones) and net deposition in areas of profile concavity (zones of decreasing flow velocity).

| | LS = (0.4+1) \( \left( \frac{A_s}{22.13} \right)^{0.4} \left( \frac{\sin \beta}{0.0896} \right)^{1.3} \) | This sediment transport capacity index was derived from unit stream power theory and is equivalent to the length-slope factor in the Revised Universal Soil Loss Equation in certain circumstances. Another form of this equation is sometimes used to predict locations of net erosion and net deposition areas.

| | CIT = \( A_s (\tan \beta)^2 \) | Variation of stream-power index sometimes used to predict the locations of headwaters of first-order streams (i.e., channel initiation). |
2.5 Detailed Descriptions of Attributes of Interest

2.5.1 Slope

Slope measures the rate of change in elevation and is typically measured as a percent rise or in units of degrees. There are a number of different methods that are used to compute slope from DEMs. Methods of calculating slope is an area which has received much attention from researchers, and for which there are many references in the literature (Jones, 1998, Horn, 1981). Two common methods are the finite differences method, and a method for computing slope based on the maximum downward slope. Conceptually, the finite differences method fits a plane to the elevation values of a 3x3 cell neighbourhood around the centre cell. The slope for the cell is computed from the 3x3 neighbourhood using an average maximum method (Burrough, 1986). The maximum downward slope method calculates the slope value based on the slope between the centre processing cell, and its lowest neighbour (Jones, 1998). Slope is significant in hydrology and geomorphology, since it has such an influence on the flux of sediment and water in a landscape (Wilson and Gallant, 2000).

2.5.2 Curvature

The curvature of a surface refers to the second derivative of a surface, or essentially the “slope of the slope”. To calculate the curvature, a fourth order polynomial is fit through the centre processing cell of a 3 x 3 window as shown in Figure 4.
Of particular interest are the plan, profile, and overall curvature values. The plan curvature is the rate of change in aspect, or the rate of change across a slope. This measure is important for investigating flow convergence and divergence on a hillslope, and is of great importance in hydrology. The profile curvature measures the rate of change in slope in the downslope direction. This attribute is important for the rate of acceleration of flow, and studies of erosion and deposition potential on a surface, and is thus of interest in hydrology and geomorphology. Total or overall curvature measures the total curvature of a surface. Where the plan and profile curvature values measure the curvature of the surface in either an across slope or downslope direction, direction is not a factor in total curvature. Total curvature is also an important attribute for the modeling of flow characteristics (Wilson and Gallant, 2000).

2.5.3 Upslope Contributing Area and Specific Catchment Area

The upslope contributing area and specific catchment area are both important hydrologically related topographic attributes. The upslope contributing area is the area
upslope of a length of contour or pixel that would contribute to flow through or over that length of contour or pixel. Closely related to the upslope contributing area is the specific catchment area (SCA). The SCA is different in that it is ratio of the contributing area to a length of contour. In the case of a pixel, the SCA is the ratio of the contributing area to the width of a pixel (Wilson and Gallant, 2000). In DEM terms, the contributing area can simply be though of the total area of cells which drain to a given cell.

2.5.4 Topographic Wetness Index

The topographic wetness index (Beven and Kirkby, 1979) is a fundamental component of some hydrologic models, as it measures the potential for soil saturation. It is calculated as the natural logarithm of the specific catchment area divided by the tangent of the local slope in degrees (Wilson and Gallant, 2000).

\[
\text{Topographic Wetness Index} = \ln \left( \frac{A_s}{\tan \beta} \right)
\]

Where \( A_s \) is the specific catchment area, and \( \beta \) is the local slope in degrees

This attribute does have a number of assumptions with it, including (from Wilson and Gallant, 2000):

- The steady-state downslope subsurface discharge is the product of average recharge and the specific catchment area
- The local hydraulic gradient can be approximated by the local slope
- The saturated hydraulic conductivity of the soil is an exponential function of depth
- Steady-state conditions are assumed
• Soil properties, specifically transmissivity are spatially uniform
• Other locations in a catchment with the same index value will have the same relationship between the local depth to the water table and mean depth
• Other areas of a catchment with the same index value will respond in a hydrologically similar way, given the same inputs

2.5.5 Stream Power Index

The stream power index is a measure of the erosive force of flowing water. Its components include the unit weight of water (which is a constant), the discharge of water per unit width (similar to specific catchment area) and the local slope.

\[
SPI = A_s \tan \beta \quad \text{Where } A_s \text{ is the specific catchment area, and} \]
\[
\beta \text{ is the local slope in degrees}
\]

This measure has been used in the past to predict ephemeral gullies, as well as to model where landscape hardening or conservation measures which would reduce soil erosion should be installed. Variations on this index have been used to predict the locations of the headwaters, or channel initiation location, of first-order streams (Wilson and Gallant, 2000).

2.6 Hydrologic Modeling and Hydrologically Conditioned DEMS

Generally, hydrologic modeling with a DEM is a multi-step process. The reasons for hydrologic modeling with a DEM are varied. In some cases, a hydrologist would be interested in the parameterization of an ecohydrological model such as RHESSys (Creed et al., 1998). Others may be interested in rainfall-runoff or flood forecasting models, or
engineering type applications. Depending on the end use and result desired, a researcher may take different steps.

Typically, the first step in conditioning a DEM for hydrologic modeling is the filling of depressions and pits in the DEM, creating a depressionless DEM. This is achieved by raising the values of cells in the depressions, sinks, or pits, to be equal in elevation with the depressions’ spill point (Jenson, 1992). Other methods used to remove depressions include depression breaching and combination methods, such as the Impact Reduction Approach which seeks to fill or breach depressions depending on which has the least impact to the original DEM (Lindsay and Creed, 2005). Depressions in a DEM can be real surface features, such as lakes, ponds, or reservoirs, or errors in the DEM resulting from interpolation or other factors. At this point, the DEM can be conditioned further to ‘encode’ the locations of known streams, or to integrate a vector stream network into a DEM. This process is generally referred to as stream burning (Saunders and Maidment, 1996). At the simplest, the DEM values are lowered or dropped where streams occur; helping to ensure that flow is routed into these cells during flow accumulation calculations. Another method is known as the AGREE method (Hellweger, 1997), where the DEM elevation value is smoothly lowered rather than abruptly lowered. This algorithm uses three important reconditioning parameters.

The first is known as the vector buffer, and the value is entered in terms of number of cells. This represents the number of cells around the linear feature class for which the smoothing will occur. The second parameter is the smooth drop/raise. This is the amount, in vertical units, that the stream will be dropped (if the number is positive) or the fence extruded (if the number is negative). This value is used to interpolate the DEM
into the buffered area (between the boundary of the buffer and the dropped/raised vector feature). The third parameter is known as the sharp drop/raise – this is the additional amount, in vertical units, that the stream will be dropped (if the number is positive) or the fence extruded (if the number is negative). This has the effect of additional burning/fencing on top of the smooth buffer interpolation. This parameter is required to ensure the preservation of the linear features used for burning/fencing (Hellweger, 1997).

The values that are used for the AGREE reconditioning parameters depend on the nature of the DEM itself, and the issues for which resolution is being sought. Often, a trial and error approach is needed before satisfactory results are obtained (Hellweger, 1997). This integration of vector data into DEMs is an active area of research, and there are many different ways it can be accomplished, often having different results.

As a typical second step, flow directions are computed for each cell in the conditioned DEM. The direction in which water will flow out of a cell into an adjacent one is encoded in the DEM according to a flow-routing algorithm (Jenson, 1992). This is a necessary step that needs to occur before a typical third step, which is the calculation of flow accumulation. This step encodes each cell with a number which represents the number of cells upstream of it that would contribute flow, based on the computed flow directions. Using this raster, and a method for determining the contributing area threshold, a fully connected stream network can be derived (Jenson, 1992).

### 2.7 Flow Routing Algorithms

The choice of flow routing algorithm in a GIS is one important component that largely determines the way in which the outflow from a given cell will be distributed to
one or more downslope cells during the flow accumulation calculation. A flow routing algorithm functions to transfer flow, including water, nutrients, and sediment, to lower (downslope) points or areas in a landscape (Desmet and Govers, 1996). Depending on the flow routing algorithm used to determine the adjacent downslope areas and points, the calculation of the primary and secondary topographic derivatives, specific catchment area, stream power index, wetness index, and other topographic indices will change. Flow routing across a surface is an active area of research, and numerous flow routing algorithms have been developed. Of these, the five most commonly used algorithms are the D8 algorithm (O’Callaghan and Mark, 1984), D-Infinity (Tarboton, 1997), Rho8 (Fairfield and Leymarie, 1991), FD8 (Quinn et al., 1991), and DEMON (Costa-Cabral and Burges, 1994). Each one of these differs in how they route flow downslope, and each will produce a different, albeit sometimes similar, stream network.

2.8 TOPMODEL

Topographic attributes, including their scale and accuracy, are important inputs to hydrologic models. TOPMODEL is one such model. TOPMODEL is based on the topographic wetness index and depends on it for its modeling where not all hydrologic models do, making the topographic wetness index an important variable in hydrologic modeling. TOPMODEL is a variable contributing area conceptual model in which the predominant factors determining the formation of runoff are represented by the topography of the basin and a negative exponential law linking the transmissivity of the soil with the vertical distance from the ground level. In this model the total flow is calculated as the sum of two terms: surface runoff and flow in the saturated zone. Chairat
and Delleur (1993) quantified the effects of DEM resolution and contour length on the distribution of the topographic wetness index as used by TOPMODEL and the model’s peak flow predictions. Wolock and Price (1994) and Zhang and Montgomery (1994) also examined the effects of DEM source scale and DEM cell spacing on the topographic wetness index and TOPMODEL watershed model predictions.

TOPMODEL represents catchment topography by means of a topographic index, \( \ln(A_s/\tan \beta) \), where ‘\( A_s \)’ is the area draining through a grid square per unit length of contour and ‘\( \tan \beta \)’ is the average outflow gradient from the square. The index is calculated from a DEM across a grid covering the catchment. The grid must be sufficiently fine to resolve important characteristics and slope formations. A high index value usually indicates a wet part of the catchment; which can arise either from a large contributing drainage area or from areas with very low slope. Areas with low index values are usually drier, resulting from either steep slope or a small contributing drainage area. Grid squares with the same index values are assumed to behave in a hydrologically similar manner.

Topography is now recognized as a first-order control on the hydrologic response of a catchment to rainfall. Topography plays an extremely important role in determining the catchment scale flow pathways resulting from the downward force of gravity (Brasington and Richards, 1998). TOPMODEL is a catchment scale rainfall-runoff model which makes an explicit link between catchment topography (and thus DEMs and related topographic attributes) and the generation of streamflow.

The model is based on a spatially distributed topographic wetness index, a compound topographic attribute that can be computed from DEMs. Apart from
TOPMODEL, the topographic wetness index is used extensively in hydrology, agriculture, geomorphology and vegetation studies, as it represents the spatial distribution of groundwater recharge areas, surface saturation potential, soil moisture, and indicates areas with potential for runoff generation (Kienzle, 2004). Water will tend to accumulate in areas with a high value of the topographic wetness index. DEM resolution is an extremely important factor in this case, since it has been noted that coarse DEMs tend to model landscapes as being wetter, whereas finer DEMs model landscapes to be drier (Wolock and McCabe, 2000). TOPMODEL results have been shown to be sensitive to DEM resolution (Brasington and Richards, 1998). Previous studies have shown significant differences in the probability distributions of topographic index computed from DEMs of different resolutions; including 12.5m and 50m (Quinn et al., 1991). Zhang and Montgomery (1994) reported that the mean of the topographic index increased progressively with DEM size, for DEM sizes ranging from 4 to 90m. Wolock and Price (1994) made the same conclusion in their study of the effect that DEM resolution and the scale of the data used to derive the DEM had on the computed topographic index.

The topographic wetness index has much influence on TOPMODEL hydrologic modeling results. The effect of DEM resolution has been investigated specifically in terms of TOPMODEL’s modeling predictions. Zhang and Montgomery (1994) found that the shift of the index towards higher values increased the rate of predicted peak streamflow.
2.9 DEM Resolution

It is well known that the grid cell size of a raster DEM has a significant effect on the elevation derivatives, such as slope, aspect, curvature and the topographic wetness index. The values of these derivatives will depend on the DEM resolution (Kienzle, 2004). In one study, Kienzle (2004) determined that both slope and soil erosion estimations increase with a decrease in the grid cell size used to derive them (Kienzle, 2004). In the study conducted by Saulnier et al. (1997), it was found that the topographic wetness index increased as the grid cell size did. Essentially, this means that catchments are modeled to be wetter when using a coarse grid cell size, and drier when using a smaller grid cell size (Saulnier quoted in Kienzle, 2004). When Zhang and Montgomery (1994) investigated two small catchments in the states of Oregon and California, with grid cell sizes ranging from 2 to 90 m, different values for slope were found. Specifically for the two catchments, a mean slope of 65% and 34% was found with the 2 m grid, as compared to 41% and 29% when using the 90 m grid (Kienzle, 2004). Further, as determined by Kienzle (2004), as grid cell size increases, the slope values get smaller. DEM’s with grid cell sizes over 25 m are not able to identify steep slopes successfully. Also, as the grid cell size increases, a considerable underestimation of slope value occurs.

In the study conducted by Brasington and Richards (1998), they found that hillslope gradient is sensitive to grid cell size, with progressively fewer cells showing a steep slope, as grid cell size increases. This is indicated through the mean slope. Brasington and Richards (1998) also looked at the effects solely on upslope contributing area (represented as \( a \)). This parameter can be defined as the total upslope area draining through a single pixel. They found that large grid cell sizes necessarily increase the
minimum contributing area (the square of the grid size), and increase the values of ln(\(a\)) as grid cell size increases. The impact of increasing grid cell size in lowering slopes and increasing contributing area is reflected in the compound topographic wetness index. As the grid cell size increases, the mean values of the topographic wetness index increased as well.

It is also accepted that different qualities of DEMs can influence a derived stream network, in addition to the stream network algorithm used. Zhou and Liu (2002), quoting Zhang and Montgomery (1994) observe that the spatial data structure of DEMs such as data precision, grid resolution and orientation affect how terrain is analyzed, including the generation of stream networks. One method suggested by Zhou and Liu (2001) is the visual comparison of derived topographic information, such as a stream network, against a ‘common knowledge’ of what would be expected, such as streams derived from a high quality orthophoto. Statistical comparison between observed and modeled attributes is also suggested.

DEM\s used in hydrologic analysis have to be of sufficient resolution to capture the variability of the terrain that they represent, as it is the terrain that plays such an efficient role in the determination of landscape flow pathways (Brasington and Richards, 1998). An increase in inexpensive computing power and hard drive storage has encouraged many to use DEM\s of high resolution.

2.10 Channel Network Characteristics

An important aspect of this work is the definition of channel network characteristics. Stream systems are a form of a network, having nodes and links and
branches that connect all of the parts together. Networks in general can be characterized and analyzed with respect to two main sets of properties. These are the topologic aspects of the network and the geometric aspects of the network. The topology of the network refers to its interconnectedness. The more relevant properties in this case are the geometric properties, which can include the length, shape, area, relief, orientation, and arrangement of the streams (Summerfield, 1991).

The most basic component of a stream network is an individual stream segment or link. A stream segment is simply a segment of a stream between two channel junctions, or in the case of a first-order stream, is a segment where flow into a network originates (i.e. it has no tributaries) (Summerfield, 1991). This concept of stream order is also of vital importance to the study of basin morphology, description of stream networks, and to applications concerning hydrologic modeling as it can be related to the relative discharge of an individual channel segment.

There have been a number of stream ordering techniques proposed by hydrologists and geomorphologists. Of these, the two most common methods are known as the Strahler ordering method, and the Shreve ordering method, with the most popular one being the Strahler method (Lindsay, 2005). The Strahler ordering method designates all stream network headwater tributaries as a first-order stream. A second-order segment is formed where two first-order segments are joined, joining two second-order segments produce a third-order segment, and so on. As a property of the Strahler ordering method, there is no increase in stream order when a particular stream segment is joined with a stream segment with a lower order. The Strahler ordering system has been found to be statistically related to important basin morphological properties in a wide range of
environments (Summerfield, 1991). Figure 5 shows the graphic representation of a Strahler ordered stream network.

![Strahler Stream Order Diagram](image)

Figure 5: Strahler Stream Ordering

The drainage (stream) density is a geometric property of a stream network, and is simply defined as the mean length of stream channels per unit area, functionally the length of streams in a watershed, divided by the watershed area (Summerfield, 1991). The drainage density is one of the most important measures of basin morphometry as well as an important indicator of the relation between climate, vegetation, and the resistance of rock and soil to erosion. The drainage density gives an idea of the resistance of the land surface to erosion by flowing water, and is related to climate and lithology. Climate is a natural factor influencing observed drainage densities. Very high
drainage densities can be observed in semi-arid environments, which are a consequence of prevalent surface runoff, and the ease with which a new channel can be originated.

The stream order is an important concept that is used to compute other stream morphology characteristics. One of these of importance to this study is a topographic metric termed the bifurcation ratio. The bifurcation ratio is defined as the ratio of the number of streams of an order to the number of streams of the next highest order, and is calculated as: \( R_b = \frac{N_i}{N_{i+1}} \). The number generally varies somewhat between different successive orders in a watershed (i.e. between first and second order, and second and third order). For this reason, a mean bifurcation ratio is usually reported for a watershed to enable comparisons. Typical values for the bifurcation ratio range between 3 and 5, with 3 considered to be theoretically normal. Bifurcation ratios as high as 10 can be observed in highly elongated watersheds with certain combinations of lithologic properties. An example would be a watershed with alternating outcrops of relatively hard and soft lithologies (Summerfield, 1991).

All metrics related to stream network topology and geometric properties are affected by the accuracy of the streams used to derive them. *Stream accuracy* is the relationship between the measured or observed stream network and the actual location of the stream network in the landscape.

**2.11 Extraction of a Stream Network from a DEM**

There is a well developed approach to hydrologic analysis using a GIS. The foundational component of all analysis is a DEM. The first step in conducting an analysis is creating a depressionless DEM, ensuring that all flow routed with the GIS is
directed to a downstream outlet, and is not “stuck” in an artificial (or natural) depression. A number of algorithms can be used to create the depressionless DEM, which is usually achieved by filling depressions or pits (Doan, 2000). Typically, when there is stream or “blue line” data of a high accuracy available, this data will be used in conjunction with the DEM to aid in the extraction of a digital stream network. There are numerous methods and algorithms used to accomplish this, none of which will be used in this work. The reason for the exclusion of this step is that the DEM itself will be evaluated for utility in digital stream network extraction, and introducing a conditioning such as this would obviously bias the result.

From the DEM, rasters of flow direction and flow accumulation can be derived. The flow direction grid partitions the surface, defining how flow, sediment, nutrients and other constituents flow over the surface from one raster cell to adjacent ones. Different algorithms exist for routing this flow, the most common being the Deterministic 8 (D-8) method. Flow accumulation can be determined using the flow direction raster, indicating how many “upslope” pixels drain through a single downslope pixel. Much methodological and empirical research has been conducted, and is being conducted now, to determine how best to extract stream networks and topographic attributes from DEMs (Tarboton, 1991). These topographic attributes and techniques form the basis for most GIS-based hydrologic modeling.

2.12 Threshold for the Extraction of Stream Networks

Numerous examples of techniques for digital channel extraction from DEMs can be found in the literature. Peuker and Douglas (1975) described a method of extracting
stream points from DEMs by flagging the pixel with the highest elevation in a window of four cells. After one complete pass of the moving window through the DEM the pixels that remain unflagged are determined to be drainage courses. One problem with technique however, is that the pixels representing the drainage courses are not necessarily connected. Band (1986) describes several improvements to this algorithm including procedures to thin and connect these potentially non-contiguous pixels. Band (1986) also described a method of flagging upwardly concave pixels in a three by three moving window, which is a change the Peuker and Douglas (1975) algorithm.

While both of these methods result in a potential drainage channel network, there is no physical basis for the network. The work of O’Callaghan and Mark (1984) suggests a physical basis for channel extraction. Their digital extraction method defines channel networks as all pixels with an accumulated area above a threshold. That is the accumulated area of all “upslope” pixels. This idea is classified as hydrologic, and works on the assumption that:

“Drainage represents those points at which runoff is sufficiently concentrated that fluvial processes dominate over slope processes. If the spatial concentration of surface runoff is simulated, then those points at which this runoff exceeds some threshold can be considered to be the drainage network” (Mark quoted in Sole and Valanzano, 1996).

The drainage network is found by determining a drainage direction matrix, identifying and removing sinks in the surface, defining a weight matrix, calculating an accumulated area matrix (based on a flow accumulation and flow routing algorithm) and selecting those pixels with a contributing area above a given threshold (O’Callaghan and Mark,
Their work does not give any indication as to what an appropriate, or physically justifiable contributing area is though.

Tarboton (1991) proposes methods for extracting digital channel networks from DEMs based on a physically justifiable accumulation area threshold. While considering that digital channels are most appropriately extracted from DEMs at a scale that is appropriate, perhaps the easiest way of determining the cumulative accumulation threshold is to compare the digital network extracted at different thresholds to the “blue lines” drawn on traditional paper maps (Tarboton, 1991). Further, one could compare channels extracted with different accumulation area thresholds to photogrammetrically mapped streams. There are arbitrary decisions made with both methods though, especially considering that most first-order streams are ephemeral and present only during the “wet season” (Strahler, 1957).

Tarboton (1991) proposes two methods for extracting the most dense or highest resolution drainage networks quantitatively, by seeking to satisfy scaling laws that have been found to hold for channel networks. These laws include a constant drop property and a power law which scales slope with area.
Chapter 3
Methodology

3.1 Methodology Overview

This chapter will describe the data sources and methods employed to answer the two research objectives specified in the first chapter. In brief, tiled raster DEM data generated from LIDAR points were acquired and merged for a watershed using ArcGIS© desktop GIS software. The resulting DEM had a resolution of 20 feet. This DEM was resampled to successively coarser resolutions. From these DEMs, the various topographic attributes to be studied were derived. These included the slope, plan curvature, profile curvature, overall surface curvature, topographic wetness index, and the stream power index. To facilitate the repetitive operations, to ensure repeatability, to reduce error, and facilitate making changes should they be needed, geoprocessing models were built using the ArcToolbox in ArcGIS©. (Appendix A)

Stream networks were derived from the DEM, by completing a process of hydrologically conditioning the DEM (ensuring the surface is conditioned to allow for downslope drainage), including only the filling of pits and depressions. Flow direction and flow accumulation rasters were created for each DEM resolution, from which streams were extracted, based on a contributing area threshold, chosen to create a stream network that most closely matched the photogrammetrically mapped stream network.
Once the computation of the topographic attributes was complete, and stream delineation was complete and repeated for each DEM, the results could be tabulated and compared.

### 3.2 Data Sources

The first methodological task was to acquire elevation data, collected through LIDAR remote sensing. Using LIDAR data would allow the comparison between high resolution data and more popular existing data sets, such as United States Geological Survey (USGS) 30m DEMs. This data was available for many parts of North Carolina; North Carolina has flown many areas of the state under the North Carolina Flood Maps program.

Also beneficial was the availability of a large-scale, high accuracy stream network for this study area, in a digital spatial format. The stream network data for Wake County, North Carolina met the National Map Accuracy Standards (NMAS) for 1:1200 data (+/- 5 ft). It is current to June 20, 2005, and was compiled by Surdex, Inc. for Wake County at a scale of 1:1200 from aerial photography at 1" = 600'. The availability of existing mapped data allowed the comparison of stream networks extracted from the DEMs, and those mapped from large scale orthophotography.
3.3 Processing

3.3.1 Resampling Original DEM

The original LIDAR DEM acquired for the study area was resampled to various coarser resolutions, including 40 feet, 80 feet, 160 feet, 320 feet and 640 feet. To effectively resample the DEMs successively to the coarser resolutions, a nearest-neighbour method was employed. The original DEM was resampled as follows, following a method used by Wolock and McCabe (2000):

- To create a 40 ft DEM, the original DEM was sampled at every second point
- To create an 80 ft DEM, the original DEM was sampled at every fourth point
- To create a 160 ft DEM, the original DEM was sampled at every eighth point
- To create a 320 ft DEM, the original DEM was sampled at every sixteenth point
- To create a 640 ft DEM, the original DEM was sampled at every thirty second point

In all cases, the resampling of the DEM from 20 ft to a coarser resolution resulted in a raster containing a loss of terrain information.

3.3.2 Computation of Terrain Attributes

Once the DEM was resampled, the topographic derivatives were calculated and compared to quantify the change. Calculation of the first terrain derivative of slope was carried out for each resolution DEM using Horn’s method (Horn, 1981) employed in ArcGIS© software. Degrees of slope were calculated, as opposed to percentages. Values for plan curvature, profile curvature, and curvature were calculated in ArcGIS© using the
CURVATURE function within ArcGIS© (Moore et. al., 1991). Each of these terrain attributes were computed for each DEM of various resolution.

Compound topographic attributes including the topographic wetness index and the stream power index were calculated in the standalone Terrain Analysis System (TAS) hydrologic and terrain analysis package (Lindsay, 2005). TAS has the algorithms for calculating these attributes built in, and completing this step in TAS rather than ArcGIS© reduced the need to manipulate data within ArcGIS©. TAS uses its own raster data format, known as a TAS Image File. Generating the TAS Image File was completed by a two step process, including the conversion of the original ArcGIS© DEM to an ASCII-format file and subsequent import of them to TAS using the “Import Raster” function. The results of the computation were a series of rasters of the topographic wetness index and stream power index for each of the various raster resolutions. The TAS image files for wetness index and stream power index were then exported from TAS as an ASCII format using the “Export Raster” function, then imported to ArcGIS© as a raster, using the ASCII to raster function in ArcToolbox.

When the six TAS images for the stream power index were converted to ASCII and then to ArcGIS© rasters, areas outside the study area acquired values of 0. In order to calculate meaningful statistics for each raster, these areas with the value of 0 outside of the study area were converted to null values, using the ArcInfo GRID SETNULL command, in the form:

\[ \text{gridnameXXnull = setnull(gridnameXX == 0, gridnameXX)} \]
This command would evaluate on a cell-by-cell basis whether a cell’s value was 0. If the expression evaluated to be true, it was given a null value, and if the expression evaluated false, it was given the existing value.

3.4 Generation of Stream Networks

In order to compare the stream networks that result from DEMs of different resolutions, a stream network was delineated for each DEM, and compared to known stream locations derived from large-scale orthophotography. To create the stream networks, the following method was employed. A well documented problem in stream network derivation from LIDAR DEMs is the effect of road banks and anthropogenic modification of the surface upon surface hydrology (Duke et al, 2003). In many cases, a road bank has been built up which serves as a dam, preventing downslope flow. In reality, a culvert or pipe is placed beneath the road bank, allowing surface runoff to maintain a route close to what is natural. However, to ensure that a derived flow network matches the natural one as closely as possible, and flow is not intercepted by the road banks, slight DEM modifications were completed to correct for this condition.

Areas where flow was unnaturally intercepted were identified and corrected. First, a hydrologically correct depressionless DEM was computed from the original 20 foot resolution DEM. This was completed by using the FILL SINKS tool in ArcGIS® software. The result was a depressionless DEM, in which there are no artificial or natural pits or sinks, ensuring that all flow in the DEM is in a downslope direction and is directed to an outlet, allowing the creation of a flow direction raster. The flow direction raster
was computed for this depressionless DEM with the D8 method (O’Callaghan and Mark, 1984).

Using the flow direction raster, a flow accumulation raster was computed for the DEM. From the flow accumulation raster a stream network was queried out by using a stream accumulation threshold or critical source threshold. An arbitrary threshold value of 400 cells to initiate a stream network was selected. Using this stream network, the derived flow was visually compared to the photogrammetrically mapped stream network, to identify those areas where flow was interrupted by a road bank or other artificial impediment. Figure 6 gives an example of this effect. Road centerlines representing road banks are green lines; a derived stream network is represented by red lines, and the photogrammetrically mapped stream network is represented by blue lines. The blue stream is observed to flow “through” the road bank, presumably diverted through a culvert, where the red lines indicate the derived flow traveling along the road bank, not following where the actual stream location is.

Figure 6: Image shows road bank impeding derived streamflow
A number of techniques were evaluated for their ability to modify the DEM in only those areas identified to have artificially interrupted flow. Of these, one method was eventually used. One of the attributes of the Wake County streams shapefile (Adler, 2001) was stream type. Of particular interest to this exercise was the ‘connector’ stream type. Connectors in this instance were identified to be artificial stream segments, such as those that are diverted through culverts and under road banks. Attempts were made to “burn” these connector streams into the original DEM, lowering the elevation values at these locations, to divert flow to the lower elevations. Once the stream burning was completed, a stream network was generated again, through the iterative process of filling depressions, deriving flow directions and accumulations. The outcome was not as intended though, with the stream network remaining unchanged. Upon careful examination of the DEM and the derived flow networks, it was obvious that a gradient needed to be used to modify the DEM in such a way that flow would be directed downslope, essentially through a funnel to a connector location. To accomplish this task, the AGREE algorithm (Hellweger, 1997) was used. In order to have the least modification of the DEM possible, a number of different reconditioning parameters were used in the reconditioning. The AGREE parameters eventually used to create the reconditioned DEM were as follows:

- Vector buffer (cells) = 10
- Smooth Drop (feet) = 5
- Sharp Drop = 5

This step used a total of only 31 connector segments which allowed the alteration of the DEM only where necessary. Reconditioning the DEM using AGREE accomplished the
task of only slightly modifying the required areas and leaving the remainder of the DEM unaltered, as well as forcing flow to flow where it should underneath road banks. The 20 foot DEM (DEM20) was reconditioned, resulting in AGREEDEM20. Pits and sinks were filled in this DEM resulting in FILLDEM20. AGREEDEM20 was resampled to 40, 80, 160, 320, and 640 foot resolutions, and each had pits and sinks subsequently filled, resulting in FILLDEM40, FILLDEM80, FILLDEM160, FILLDEM320, and FILLDEM640. Each AGREEDEM had sinks and pits filled, as the resampling process introduces small pits and sinks during its execution. These DEMs became the ones to be used in the final stream network generation and analysis, and watershed delineation.

To prevent simply choosing an arbitrary stream accumulation threshold, a series of stream networks were calculated for FILLDEM20 based on values of a stream accumulation threshold of 200 to 700 cells. The resulting stream networks were compared visually to determine which one most closely resembled the photogrammetrically mapped stream network in terms of the initiation point of first order streams. The stream accumulation threshold eventually chosen was 400 cells to initiate a stream network. This equates to 160,000 square feet, or 1.5 ha. The following table gives the number of cells at each resolution, used to initiate and derive a stream network.

Table 3: Number of cells to initiate a stream network

<table>
<thead>
<tr>
<th>Cell Size (ft)</th>
<th>Number of cells to initiate a stream</th>
<th>Corresponding square feet</th>
<th>Hectares</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>400</td>
<td>160000</td>
<td>1.49</td>
</tr>
<tr>
<td>40</td>
<td>100</td>
<td>160000</td>
<td>1.49</td>
</tr>
<tr>
<td>80</td>
<td>25</td>
<td>160000</td>
<td>1.49</td>
</tr>
<tr>
<td>160</td>
<td>6</td>
<td>153600</td>
<td>1.43</td>
</tr>
<tr>
<td>320</td>
<td>2</td>
<td>204800</td>
<td>1.90</td>
</tr>
</tbody>
</table>
Following the generation of the stream network, the Strahler stream order was assigned to the stream links in the network through the STREAMORDER tool present in *ArcGIS* \(^\text{\textcopyright}\) software, for each resolution. The resulting stream network was then converted to the vector stream features in *ArcGIS* \(^\text{\textcopyright}\) using the Streams to Feature tool (without simplification) so that this data was available for subsequent analysis.

### 3.5 Comparison of Topographic Attributes

A number of descriptive, quantitative and qualitative results were compiled and reported. For the topographic attributes slope, plan curvature, profile curvature, surface curvature, topographic wetness index, and the stream power index, descriptive statistics including mean, maximum, minimum, and standard deviation were calculated using *ArcGIS* \(^\text{\textcopyright}\) and reported in tabular format. The Cumulative Frequency Distributions (CFDs) of each of these attributes were graphed to observe any visual difference in the distributions.

To enable a visual comparison of the effect of resolution on terrain attributes, profile charts were created to show how the values of a terrain attribute vary over a two-mile transect of the watershed. First, the location of a two-mile transect was identified that included variation in the terrain observed through inspection of the 20 foot DEM with a hill shaded rendering applied. The location of the transect on the surface is shown in Figure 7. The LIDAR Data Handler ArcMap \(^\text{\textcopyright}\) extension (NOAA) was then used to extract the terrain attribute value every 20 feet from every raster for all attributes and resolutions. This data was then exported to a commercial spreadsheet software package for creation of the profile charts.
To enable a more statistical comparison, the statistical distributions of each of the topographic attributes were compared using a statistical test known as the Kolmogorov-Smirnov (K-S) test. This statistical test is used to determine if there is a significant difference between two CFDs. The test was conducted on the CFDs for each topographic attribute at different resolutions, to compare and determine if there is a significant difference in the distributions. The tests were conducted using the Terrain Analysis System (TAS) software.

3.6 Strahler Stream Ordering of Photogrammetrically Mapped Streams

While ArcGIS© has the facility to attribute a raster stream network with Strahler stream order information when derived from an available DEM, the base software product cannot accomplish the ordering of vector stream networks without customization. In order to compare, by Strahler order, the streams that are delineated from the DEM surface in the GIS, and those vectors of streams acquired through photogrammetric mapping methods, the vector streams need to have an order value assigned to them. This task was completed using a customized software product named RivEx (http://www.rivex.co.uk). Some minor modifications to the stream network were required to allow the software to correctly identify the stream order. First, all stream segments were checked to ensure that they flow in the proper downstream direction. The original stream network was also constructed in such a way that there could be several physical stream segments that comprise one actual stream. This could cause the count of stream segments to be wrong. To avoid this problem, all pseudo-nodes were removed from the original stream network. This ensured that any given physical stream segment
was represented by only one line in the GIS. The ordered streams were then used to compare the spatial location and orders of analytically delineated streams.

3.7 Calculation of the Bifurcation Ratio and Stream Length Ratio

The calculation of the bifurcation ratio was completed for streams delineated from DEMs of the various resolutions as well as the photogrammetrically mapped stream network. The number of stream segments in each stream order for each stream network was summarized in ArcGIS© software and the bifurcation ratios were manually calculated. The lengths of all streams by order were summarized in ArcGIS© for each stream network giving a total of all first-order through sixth-order streams, for all networks. The stream length ratios were then calculated manually (Tarboton, 1996).

3.8 Comparison of Stream Location Agreement using the Kappa Index of Agreement

The Kappa Index of Agreement (KIA) is a statistical test that can be used to test raster independence, and to quantify the similarity (or dissimilarity) of rasters. The KIA is a number between 0 and 1, with a higher number indicating more agreement (Chuang, 2001). The KIA was used to compare the stream network generated through automated delineation from the 20 foot DEM, with the photogrammetrically mapped stream network (Melville and Martz, 2004). To facilitate this, the rasters being compared need to have the same resolution, and need to have the same origin and alignment. The original vector photogrammetrically mapped stream network was converted to a raster format using a cell size of 20 feet, using the 20 foot DEM as a base to snap to.
The KIA was determined for overall raster agreement and for agreement by order through processing in ArcGIS®. Essentially, a cross-tabulation of the rasters was performed to generate the KIA statistic. Each raster was converted to a Boolean stream network raster, where the value of 1 represented a stream cell, and 0 represented a non-stream cell. Through a map algebra combine operation, the stream agreement could be determined. The output of the operation is a matrix showing the four potential combinations of the agreement, including 0-0 (not streams in both stream rasters), 1-0 or 0-1 (a stream in one raster but not the other) and 1-1 (a stream in both rasters indicating agreement). Using this matrix, the KIA was determined.

To facilitate the generation of KIA by order, a map algebra 'combinatorial and' operation was completed with the photogrammetrically mapped streams raster and the streams derived from the 20 foot DEM. This operation resulted in a table showing giving a unique value to cell overlap, by order. This table provided the data to generate a matrix showing stream agreement by order, and the subsequent generation of the KIA for each order of stream. This same matrix was used to generate the KIA for the derived and mapped stream network considering all orders.

The KIA was only calculated for the results of the stream network generated from the 20 foot DEM. Although the KIA is a flexible statistic used in a great number of areas and disciplines, in this context the KIA only works on raster data and using a single cell size in the analysis is a requirement. This makes it impractical to compare the results of a stream network generated from cell sizes of many resolutions (i.e. 40, 80, 160, and 320) to the rasterized photogrammetrically mapped stream network, with a cell size of 20 feet.
Although the KIA is a very good measure of agreement, another method was required to compare the agreement across all resolutions.

### 3.9 Vector Analysis of Stream Agreement

In order to facilitate the comparison of stream networks delineated from rasters with different resolutions, and the streams that were photogrammetrically mapped, the different networks were compared quantitatively. There were a number of steps involved in the processing to accomplish this. First, the photogrammetrically mapped streams were ordered using the RivEx stream ordering tool, which assigned each unique stream arc a Strahler order attribute. Each of the raster stream networks that were derived from the DEMs of increasingly coarse resolutions were converted to vector stream networks through processing in ArcGIS©. Then, the photogrammetrically mapped streams were buffered by 20 feet, the smallest DEM cell size used in the study, and the buffers were concurrently dissolved based on the stream order attribute. There was a small overlap of the buffers that occurred where stream segments connect, meaning that in a very few areas, it is possible for a stream segment to be located in more than one buffer, and attributed to the buffer of a stream network to which it does not belong. Each of the vector stream networks at the various resolutions were then intersected with the buffered photogrammetrically mapped streams through a process similar to that employed by Kenny and Matthews (2005). This process assigned each stream segment that intersected the buffer with the length within and the order of the buffer it intersected. By determining where the Strahler stream attribute from the vectorized stream networks matched the Strahler attribute from the buffered streams, a matrix of agreement was
constructed. This matrix shows the lengths by order of the stream segments that were intercepted correctly. This matrix also supports the calculation of the percentage, by length, of correct interception.
Chapter 4
Results and Discussion

4.1 Topographic Attributes

For all the terrain attributes, descriptive statistics were generated for the extent of the study watershed. Depending on the attribute, different statistics were graphed to visually show the trend. There was no general pattern found that was consistent for all derivatives. Instead, each computed derivative showed a different resolution dependency.

In order to visualize how the values for computed terrain derivatives change over the surface at different cell sizes profile graphs were created for each attribute. Figure 7 shows the location of the transect on the surface along which each attribute was extracted.
For each topographic attribute a cumulative distribution function was created.
The cumulative frequency distributions (CFDs) show each topographic attribute’s values,
at each DEM resolution, as a percentage of the terrain surface. In general, the cumulative

Figure 7: Profile Transect Location in Watershed
frequency diagrams are excellent indicators of changes in the distribution of the various
terrain attributes at different resolutions. The diagrams are further indication of the
direction of change (if any) in the values at each cell size. In some cases, there is an
expected parallel shift in the CFD graph for a terrain attribute such as the topographic
wetness index. For others, like the curvature parameters where the curvature values are
expected to become limited when computed from an increased cell size, the diagrams will
show high representation at extreme values of curvature for cell sizes, and very little
variation at higher cell sizes.

The Kolmogorov-Smirnov (K-S) test was completed on each CFD for each terrain
attribute. The rationale for this was to determine if there was a significant difference in
the cumulative distribution of the terrain derivatives when derived from DEMs of
increasingly coarse resolutions. These results are presented in tabular format and their
significance discussed below.

4.1.1 Elevation

Figure 8 depicts the change in elevation representation along the two-mile
transect. Represented elevation values are observed to change and variability is reduced
when represented in increasingly coarse DEMs. In some areas, represented elevations
increase. At high resolutions, including those between 20 and 160 feet, the elevations are
represented in a very similar way, and there is fine variability represented. The 320 foot
DEM however begins to show a large loss of detail in terrain variability, although abrupt
and large elevation changes can be identified. Elevation values are not realistically
represented in the 640 foot DEM however; far too much detail is lost, and even abrupt
and large changes in elevation are not easily identified. In this case, the cell size is simply too large to represent the fine variability. Over a length of about two miles, only 11 cells of 640 feet are used to represent the terrain, whereas 528 cells of 20 feet are used over the same distance.

![Elevation Variation by Cell Size over Transect](image)

**Figure 8: Elevation Variability along a Transect at Different Cell Sizes**

As indicated in Table 4, there is little change in the computed statistics for elevation. The mean value stays very constant with values of approximately 369 feet across all cell sizes. Additionally, there is little observed variation in the standard deviation across cell sizes as values range from 59.18 feet for the 20 foot cell size, to a lower value of 57.9 feet at a cell size of 640 feet. Larger effects of cell size are noted for the minimum and maximum elevation values at each cell size. The minimum elevation
value ranges from 203.87 feet for the 20 foot DEM to 211.41 feet for the 640 foot cell size. Maximum elevation values exhibited a slightly higher range of values, with the maximum value computed to be 519.1 feet computed from the 20 foot DEM, and 502.78 feet computed from the 640 foot DEM. This generally indicates that maximum elevation becomes slightly underestimated when represented by a larger cell size DEM, and the minimum elevation is slightly overestimated when derived from a larger cell size DEM. This is expected, as resampling uses the exact same elevation values for a much smaller number of cells. The relationship between represented elevation values and cell size is shown in Figure 9; indicating that elevation is not very resolution dependent, as expected.

The trends in observed minimum and maximum elevation values are global. If just a single cell representing a maximum or minimum elevation value is not selected in the resampling, this could explain the change in maximum and minimum values.

Table 4: Summary statistics for elevation

<table>
<thead>
<tr>
<th>Cell Size (ft)</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Range</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>203.874</td>
<td>518.098</td>
<td>314.224</td>
<td>369.760</td>
<td>59.184</td>
</tr>
<tr>
<td>40</td>
<td>204.088</td>
<td>517.437</td>
<td>313.349</td>
<td>369.750</td>
<td>59.182</td>
</tr>
<tr>
<td>80</td>
<td>206.469</td>
<td>516.465</td>
<td>309.996</td>
<td>369.821</td>
<td>59.117</td>
</tr>
<tr>
<td>160</td>
<td>207.052</td>
<td>509.508</td>
<td>302.456</td>
<td>369.586</td>
<td>58.944</td>
</tr>
<tr>
<td>320</td>
<td>208.689</td>
<td>507.451</td>
<td>298.763</td>
<td>369.939</td>
<td>58.620</td>
</tr>
<tr>
<td>640</td>
<td>211.412</td>
<td>502.783</td>
<td>291.371</td>
<td>369.324</td>
<td>57.897</td>
</tr>
</tbody>
</table>
Figure 9: Minimum and Maximum Computed Elevation by Cell Size

Figure 10 shows the CFD for the elevation values in the watershed. As indicated by the graph, there is virtually no change in the cumulative distribution for the parameter. The same shape is shown in the distribution for each cell size. The cumulative frequency of elevation values do not change with a change in cell size.
As observed through the descriptive statistics, and through an examination of the CFDs, there is very little difference in the mean elevation values, or the CFD for elevation. This is confirmed by the results of the K-S test for elevation. The D-Max values are extremely small between the CFD for each cell size, although they do increase progressively as the cell sizes increase. This indicates an increasing difference in the distributions, though not enough to be significant, as indicated by the significance values. The CFD difference for elevation across cell sizes is statistically insignificant.
4.1.2 Slope

The slopes represented by different cell sizes change in response to the cell size from which they are derived. The steepest slope identified in the profile is a slope of about 23 degrees, at a distance of about 5800 feet from the start of the transect, as shown in Figure 11. All of the peak slopes are identified from the 20 foot DEM. As cell size increases though, there is much less slope variability present represented on the surface. Between cell sizes 20 and 80, the slopes represented consistently decrease, through they still appear to represent the overall picture of slope on the surface, as compared to that derived from the 20 foot DEM. At cell sizes of 320 and 640 feet though, there is a distinct “flattening” of the terrain, and there is very little variability shown. This reduced representation of slope in the landscape has many hydrologic implications, including changes in erosion potential, and potential soil saturation.
The effect of grid cell size on slope is very substantial as shown in Table 6 and Figure 12. There is a very obvious change in the maximum, mean, and standard deviation values, indicating that slope decreases when computed from a DEM with a large cell size and these same DEMs are not able to identify areas of steep slope successfully. Maximum computed values of slope range from a high of 56.91 degrees when computed from a 20 foot DEM to a low of 9.19 degrees for the 640 DEM. Mean and standard deviation values also fall steadily from a high of 3.56 degrees to 2.98 degrees, and 3.03 degrees to 2.19 degrees respectively. This relationship can also be readily understood from Figure 12. Mean slope falls consistently from small cell sizes to
large ones, however, the maximum computed slope value falls sharply from small cell size to large ones.

Table 6: Summary statistics for slope

<table>
<thead>
<tr>
<th>Cell Size (ft)</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Range</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>0.000</td>
<td>56.911</td>
<td>56.911</td>
<td>3.560</td>
<td>3.026</td>
</tr>
<tr>
<td>40</td>
<td>0.000</td>
<td>37.614</td>
<td>37.614</td>
<td>3.332</td>
<td>2.704</td>
</tr>
<tr>
<td>80</td>
<td>0.000</td>
<td>27.012</td>
<td>27.012</td>
<td>2.976</td>
<td>2.194</td>
</tr>
<tr>
<td>160</td>
<td>0.001</td>
<td>17.656</td>
<td>17.655</td>
<td>2.495</td>
<td>1.631</td>
</tr>
<tr>
<td>320</td>
<td>0.021</td>
<td>9.188</td>
<td>9.167</td>
<td>1.865</td>
<td>1.096</td>
</tr>
<tr>
<td>640</td>
<td>0.004</td>
<td>5.288</td>
<td>5.284</td>
<td>1.277</td>
<td>0.708</td>
</tr>
</tbody>
</table>

Figure 12: Maximum and Mean Computed Slope by Cell Size

In order to clearly show the trend of mean slope values, the mean slope values for each cell size are shown separately in Figure 13, along with a log-trend line, formula and R² value for the relationship.
Figure 13: Mean Computed Slope by Cell Size with Log Trend Line

Figure 13 shows a very strong log relationship between cell size and mean slope, as indicated through the very large $R^2$ value of 0.9731.

The CFD of slope is shown in Figure 14. Unlike elevation, the values for slope appear to be very sensitive to changes in the cell size from which they are derived. The arrow in Figure 14 indicates the leftward movement of the CFD to progressively lower values of slope as cell size increases. These curves appear to be transformed versions of each other suggesting that the entire distribution, not just the mean, follows a relatively simple dependency on resolution. Slope is underestimated at large cell sizes, there is a smaller range of values of slope at large cell sizes, and there are distinctly fewer high values of slope computed from larger cell sizes.
For the slope attribute, the D-Max statistic increases steadily as the cell size does, indicating an increasing difference in the CFD, and a greater maximum difference as cell size increases.
4.1.3 Overall Curvature

Figure 15 shows the curvature values over the transect. As also evidenced through an examination of the descriptive statistical values for the curvature parameters over the whole watershed, the curvature of the surface is greatly reduced, and the values of curvature become limited as cell size increases. When computed from a 20 foot DEM, there are many peaks and valleys in the curvature graph, indicating relatively large values of negative and positive curvature, indicating a high rate of change in slope for many locations over the transect. As cell sizes increase, this variability quickly falls off, and values for the curvature parameters begin to stay very close to the value of zero; increasingly so as the cell size increases. At the cell size of 40 feet, there is limited change in the curvature and very little curvature evident when computed from the 80 foot DEM. The graphed lines for the curvature parameters appear to be indistinguishable from zero when computed from DEMs at 320 and 640 feet.
Overall curvature values decrease greatly when computed using large cell sizes. Descriptive statistics for curvature are given in Table 8. The mean curvature remains constant across all cell size ranges. This is expected, as globally the negative curvature values will balance with the positive values. The outer bound of minimum and maximum value for curvature as computed from each DEM become very limited in value. When computed from a 20 foot DEM, the minimum curvature is -21.82 m m$^{-2}$ (upwardly concave) and the maximum curvature is 40.07 m m$^{-2}$ (upwardly convex), indicating a terrain surface with extensive curvature. However, when computed from a 640 foot DEM, the minimum computed value is -0.035 m m$^{-2}$ and the maximum value is 0.035 m m$^{-2}$.
indicating a terrain surface with virtually no curvature. Values for the standard deviation fall steadily as cell size increases, indicating a reduction in the spread of different values, and the reduction in curvature variability. Figure 16 shows the convergence of the curvature values as cell size increases. While there is a large gap between minimum and maximum values at the 20 foot cell size, this gap disappears as cell size increases, showing very little curvature representation when computed from 80 foot or larger DEMs.

Table 8: Summary statistics for curvature

<table>
<thead>
<tr>
<th>Cell Size (ft)</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Range</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>-21.815</td>
<td>40.074</td>
<td>61.888</td>
<td>0.000001</td>
<td>0.331</td>
</tr>
<tr>
<td>40</td>
<td>-6.783</td>
<td>17.066</td>
<td>23.849</td>
<td>0.000069</td>
<td>0.197</td>
</tr>
<tr>
<td>80</td>
<td>-1.011</td>
<td>1.019</td>
<td>2.030</td>
<td>-0.000056</td>
<td>0.085</td>
</tr>
<tr>
<td>160</td>
<td>-0.330</td>
<td>0.479</td>
<td>0.808</td>
<td>-0.000152</td>
<td>0.044</td>
</tr>
<tr>
<td>320</td>
<td>-0.111</td>
<td>0.174</td>
<td>0.284</td>
<td>-0.000055</td>
<td>0.021</td>
</tr>
<tr>
<td>640</td>
<td>-0.035</td>
<td>0.035</td>
<td>0.070</td>
<td>-0.000051</td>
<td>0.008</td>
</tr>
</tbody>
</table>

Curvature Values for each Cell Size

Figure 16: Maximum and Minimum Computed Curvature by Cell Size
Figure 17 show the cumulative frequencies of the values for curvature. The distribution shows a very similar pattern, just as was observed through an examination of the descriptive statistics of the values, and the values along a two-mile transect of the watershed. At small cell sizes, there are relatively large values of curvature. These become increasingly smaller, and limited in their variability as cell sizes increase. The curvature parameter is strongly underestimated as cell size increases, with values tending to zero as the cell size increases. With larger cell sizes in the DEM, it becomes very difficult to identify areas with large concavity values, or convexity values, both of which are important to hydrologic studies and hydrologic modeling as they are strong indicators of areas of flow convergence, and flow divergence and dispersion on the terrain surface. The arrows in Figure 17 indicate the direction of the convergence of the values at increasingly coarse cell sizes.

![Figure 17: CFD for Curvature](image)

Figure 17: CFD for Curvature
Table 9: Results of the Kolmogorov-Smirnov Test on the Curvature

<table>
<thead>
<tr>
<th>Curvature</th>
<th>D Max</th>
<th>Occurred At</th>
<th>Total n</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 and 40</td>
<td>0.1093</td>
<td>0.12697600</td>
<td>5812588</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 80</td>
<td>0.2518</td>
<td>0.08297729</td>
<td>4940048</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 160</td>
<td>0.3354</td>
<td>0.06097412</td>
<td>4721865</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 320</td>
<td>0.4119</td>
<td>0.03697968</td>
<td>4667344</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 640</td>
<td>0.4736</td>
<td>0.01872253</td>
<td>4653712</td>
<td>0.001</td>
</tr>
</tbody>
</table>

The same trend is observed for the curvature attribute as well, which is consistent with earlier observations the behavior of the attribute through an examination of the elementary statistics and the graph of the CFD. As the cell size is increased, there is an increase in the maximum distance between the frequency distributions.

4.1.4 Plan Curvature

Figure 18 shows the plan curvature values over the transect. As also evidenced through an examination of the descriptive statistical values for the curvature parameters over the whole watershed, the plan curvature of the surface is greatly reduced, and the values of plan curvature become limited as cell size increases. When computed from a 20 foot DEM, there are many peaks and valleys in the curvature graph, indicating relatively large values of negative and positive curvature, indicating a high rate of change in slope for many locations over the transect. As cell sizes increase, this variability quickly falls off, and values for the plan curvature parameters begin to stay very close to the value of zero; increasingly so as the cell size increases. At the cell size of 40 feet, there is limited change in the plan curvature and very little plan curvature evident when computed from the 80 foot DEM. The graphed lines for the plan curvature parameter appear to be indistinguishable from zero when computed from DEMs at 320 and 640 feet.
Plan curvature, a component of overall curvature shows the same general pattern as seen for overall curvature. As shown in Table 10, as the cell size increases, there is an observed decrease in plan curvature represented in the terrain surface. As expected, the mean values for plan curvature remain steady with values very close to zero. The range of values as indicated by the standard deviation also become very limited as cell size increases. Minimum and maximum values at the 20 foot cell size are smaller than seen for overall curvature, at -13.04 m m$^{-2}$ (upwardly concave in the plan direction) and 25.82 m m$^{-2}$ (upwardly convex in the plan direction) respectively, with values again near zero when computed from the 640 foot DEM. Effectively, the larger DEM cell sizes strongly limit the plan curvature on the surface. As with overall curvature, the plan curvature...
values converge when computed from larger cell sizes, as shown in Figure 19. Above an 80 foot cell size, there is virtually no curvature represented in the DEM whatsoever.

Table 10: Summary statistics for plan curvature

<table>
<thead>
<tr>
<th>Cell Size (ft)</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Range</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>-13.039</td>
<td>25.819</td>
<td>38.858</td>
<td>-0.000184</td>
<td>0.169</td>
</tr>
<tr>
<td>40</td>
<td>-3.932</td>
<td>8.401</td>
<td>12.333</td>
<td>0.000359</td>
<td>0.101</td>
</tr>
<tr>
<td>80</td>
<td>-0.715</td>
<td>0.761</td>
<td>1.477</td>
<td>0.000753</td>
<td>0.046</td>
</tr>
<tr>
<td>160</td>
<td>-0.310</td>
<td>0.297</td>
<td>0.607</td>
<td>0.000590</td>
<td>0.025</td>
</tr>
<tr>
<td>320</td>
<td>-0.077</td>
<td>0.091</td>
<td>0.167</td>
<td>0.000329</td>
<td>0.012</td>
</tr>
<tr>
<td>640</td>
<td>-0.018</td>
<td>0.022</td>
<td>0.040</td>
<td>0.000102</td>
<td>0.005</td>
</tr>
</tbody>
</table>

Figure 19: Maximum and Minimum Computed Plan Curvature by Cell Size

Figure 20 show the cumulative frequencies of the values for plan curvature. The distribution shows a very similar pattern, just as was observed through an examination of the descriptive statistics of the values, and the values along a two-mile transect of the
watershed. At small cell sizes, there are relatively large values of plan curvature. These become increasingly smaller, and limited in their variability as cell sizes increase. The curvature parameter is strongly underestimated as cell size increases, with values tending to zero as the cell size increases. With larger cell sizes in the DEM, it becomes very difficult to identify areas with large concavity values, or convexity values, both of which are important to hydrologic studies and hydrologic modeling as they are strong indicators of areas of flow convergence, and flow divergence and dispersion on the terrain surface. The arrows in Figure 20 indicate the direction of the convergence of the values at increasingly coarse cell sizes.

Figure 20: CFD for Plan Curvature
Table 11: Results of the Kolmogorov-Smirnov Test on the Plan Curvature

<table>
<thead>
<tr>
<th>Plan Curvature</th>
<th>D Max</th>
<th>Occurred At</th>
<th>Total n</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 and 40</td>
<td>0.1069</td>
<td>0.06827042</td>
<td>5812588</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 80</td>
<td>0.2348</td>
<td>0.04299930</td>
<td>4940048</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 160</td>
<td>0.3122</td>
<td>0.03305892</td>
<td>4721865</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 320</td>
<td>0.3906</td>
<td>0.02142961</td>
<td>4667344</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 640</td>
<td>0.4587</td>
<td>0.01077697</td>
<td>4653712</td>
<td>0.001</td>
</tr>
</tbody>
</table>

The same trend is observed for the plan curvature attribute as well, which is consistent with earlier observations the behavior of the attribute through an examination of the elementary statistics and the graph of the CFD. As the cell size is increased, there is an increase in the maximum distance between the frequency distributions.

4.1.5 Profile Curvature

Figure 21 shows the profile curvature values over the transect. As also evidenced through an examination of the descriptive statistics values for the profile curvature parameters over the whole watershed, the profile curvature of the surface is greatly reduced, and the values of profile curvature become limited as cell size increases. When computed from a 20 foot DEM, there are many peaks and valleys in the profile curvature graph, indicating relatively large values of negative and positive curvature, indicating a high rate of change in slope for many locations over the transect. As cell sizes increase, this variability quickly falls off, and values for the profile curvature parameter begins to stay very close to the value of zero; increasingly so as the cell size increases. At the cell size of 40 feet, there is limited change in the profile curvature and very little profile curvature evident when computed from the 80 foot DEM. The graphed lines for the
curvature parameters appear to be indistinguishable from zero when computed from DEMs at 320 and 640 feet.

![Profile Curvature Variation by Cell Size over Transect](image)

**Figure 21: Profile Curvature Variability along a Transect at Different Cell Sizes**

Profile curvature, a component of overall curvature shows the same general pattern as seen for overall and plan curvature, as is expected. As the cell size increases, there is an observed decrease in computed profile curvature represented in the terrain surface. As expected, the mean values for profile curvature remain steady with values very close to zero. The range of values as indicated by the standard deviation also become very limited as cell size increases. Minimum and maximum values at the 20 foot cell size are smaller than seen for overall curvature, at -18.47 m m$^{-2}$ (upwardly concave in
the profile direction) and 12.36 m m^-2 (upwardly convex in the profile direction)
respectively, with values again near zero when computed from the 640 foot DEM.
Effectively, the larger DEM cell sizes strongly limit the profile curvature on the surface.
As with overall curvature, the profile curvature values converge when computed from
larger cell sizes, as shown in Figure 22. Above an 80 foot cell size, there is virtually no
curvature represented in the DEM whatsoever.

Table 12: Summary statistics for profile curvature

<table>
<thead>
<tr>
<th>Cell Size (ft)</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Range</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>-18.471</td>
<td>12.363</td>
<td>30.834</td>
<td>-0.000185</td>
<td>0.216</td>
</tr>
<tr>
<td>40</td>
<td>-8.666</td>
<td>4.201</td>
<td>12.866</td>
<td>0.000290</td>
<td>0.125</td>
</tr>
<tr>
<td>80</td>
<td>-0.632</td>
<td>0.696</td>
<td>1.328</td>
<td>0.000809</td>
<td>0.054</td>
</tr>
<tr>
<td>160</td>
<td>-0.296</td>
<td>0.237</td>
<td>0.533</td>
<td>0.000742</td>
<td>0.027</td>
</tr>
<tr>
<td>320</td>
<td>-0.091</td>
<td>0.078</td>
<td>0.169</td>
<td>0.000385</td>
<td>0.012</td>
</tr>
<tr>
<td>640</td>
<td>-0.024</td>
<td>0.021</td>
<td>0.046</td>
<td>0.000153</td>
<td>0.005</td>
</tr>
</tbody>
</table>

Profile Curvature Values for each Cell Size

Figure 22: Maximum and Minimum Computed Profile Curvature by Cell Size
Figure 23 show the cumulative frequencies of the values for profile curvature. The distribution shows a very similar pattern, just as was observed through an examination of the descriptive statistics of the values, and the values along a two-mile transect of the watershed. At small cell sizes, there are relatively large values of curvature. These become increasingly smaller, and limited in their variability as cell sizes increase. The profile curvature parameter is strongly underestimated as cell size increases, with values tending to zero as the cell size increases. With larger cell sizes in the DEM, it becomes very difficult to identify areas with large concavity values, or convexity values, both of which are important to hydrologic studies and hydrologic modeling as they are strong indicators of areas of flow convergence, and flow divergence and dispersion on the terrain surface. The arrows in Figure 23 indicate the direction of the convergence of the values at increasingly coarse cell sizes.

Figure 23: CFD for Profile Curvature
Table 13: Results of the Kolmogorov-Smirnov Test on the Profile Curvature

<table>
<thead>
<tr>
<th>Profile Curvature</th>
<th>D Max</th>
<th>Occurred At</th>
<th>Total n</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 and 40</td>
<td>0.1071</td>
<td>-0.07232885</td>
<td>5812588</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 80</td>
<td>0.2483</td>
<td>-0.04712323</td>
<td>4940048</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 160</td>
<td>0.3359</td>
<td>-0.03424690</td>
<td>4721865</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 320</td>
<td>0.4131</td>
<td>-0.02057295</td>
<td>4667344</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 640</td>
<td>0.4724</td>
<td>-0.01124588</td>
<td>4653712</td>
<td>0.001</td>
</tr>
</tbody>
</table>

The same trend is observed for the profile curvature attribute as well, which is consistent with earlier observations the behavior of the attribute through an examination of the elementary statistics and the graph of the CFD. As the cell size is increased, there is an increase in the maximum distance between the frequency distributions.

4.1.6 Stream Power Index

The profile graph of the stream power index is shown in Figure 24. The results are most interesting when viewed in the context of the related terrain derivatives, especially elevation and slope. Beginning at about distance 2600 along the transect, there is a deep valley, as indicated in Figure 8, and is an area characterized by steep slopes as shown in Figure 11. In Figure 24, this same area is shown to have a large value for the stream power index, at the 640 foot cell size. This is also evident, at the smaller cell sizes, at locations of other smaller valleys at approximately 6120 feet and 9000 feet along the transect. Generally, there seems to be more peaks associated with the stream power index graphs at smaller cell sizes, most likely due to the fine variability of slopes and specific catchment area at these smaller cell sizes. The spikes are generally not observed in the graph when stream power index is computed from larger cell sizes.
Figure 24: Stream Power Index Variability along a Transect at Different Cell Sizes

The resolution dependencies of the values for the stream power index are completely different from those noted for the other terrain derivatives, as reported in Table 14. The minimum values for the stream power index are constant at or near zero. The maximum values however, reflect the inverse of what is observed for both the mean and standard deviation values. For instance, the maximum computed value for the stream power index is 4412.62 from the 20 foot DEM, with a steady fall in the computed values to a maximum value of 1300.89 observed from the 640 foot DEM. This behavior is the inverse of the observation for the mean stream power index values, which have a steady increase in value, from a low of 7.25 for the 20 foot DEM to a mean value of 29.81 for the 640 foot DEM. The standard deviation values increase with an increase in cell size as
well, indicating a greater spread of value when computed from a DEM with a larger cell size. The rise in mean values for the stream power index is not unexpected, as the values are proportional to the increased specific catchment area values computed from increasingly coarse DEMs. This steady increase in the mean value of stream power index with coarser DEMs is shown in Figure 25. While the difference in value is small between the 20 foot and 40 foot DEMs, and the 320 foot and 640 foot DEMs, there is a much larger observed increase between the 80 foot, 160 foot, and 320 foot DEMs. The maximum stream power index value declines sharply for the 320 and 640 foot DEMs. This correlates with the decrease in maximum slope observed in Table 6. The very low maximum slope values at lower resolutions could explain the large drop in maximum stream power index values as slope is directly related to the stream power index.

Table 14: Summary statistics for stream power index

<table>
<thead>
<tr>
<th>Cell Size (ft)</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Range</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>0.000</td>
<td>4412.630</td>
<td>4412.630</td>
<td>7.253640</td>
<td>31.771</td>
</tr>
<tr>
<td>40</td>
<td>0.000</td>
<td>2411.780</td>
<td>2411.780</td>
<td>9.601110</td>
<td>34.054</td>
</tr>
<tr>
<td>80</td>
<td>0.000</td>
<td>3821.980</td>
<td>3821.980</td>
<td>16.030400</td>
<td>59.481</td>
</tr>
<tr>
<td>160</td>
<td>0.001</td>
<td>3649.560</td>
<td>3649.560</td>
<td>23.195600</td>
<td>80.383</td>
</tr>
<tr>
<td>320</td>
<td>0.100</td>
<td>2060.890</td>
<td>2060.790</td>
<td>28.669100</td>
<td>78.388</td>
</tr>
<tr>
<td>640</td>
<td>0.045</td>
<td>1300.890</td>
<td>1300.850</td>
<td>29.805600</td>
<td>62.200</td>
</tr>
</tbody>
</table>
As shown in Figure 25 above, there is a clear increase in the mean stream power index when computed from DEMs of increasingly coarse resolution. As noted in Table 14, there is a small increase in mean stream power index between the 20 foot and 40 foot cell size. Between the 40 foot and 80 foot cell sizes, and the 80 foot and 160 foot cell sizes, there is a much larger increase in mean stream power index. As predicted, the stream power index increases as cell size increases. This is a function of the increase in the specific catchment area in DEMs with large cell sizes. Above 320 feet, there is a very slight increase in the stream power index, as it seems to reach a sill. Perhaps this is indicative that 409,600 square feet is near the largest specific catchment area, represented by a single 640 foot cell.

Figure 26 shows the CFDs for the stream power index as computed from DEMs of each cell size. There is a general parallel shift to the right for the values, moving from
a small cell size to a large cell size, showing progressively higher values for the stream power index computed from DEMs with large cell sizes. These curves confirm that the entire distribution is sensitive to cell size, not just the mean values. The frequency distribution becomes smoother as cell size increases, not showing the large number of small values of stream power index as the frequency distribution for the values derived from the 20 foot DEM show. Generally, at each cell size, about 70% of the values appear to be under 20, with a much smaller percentage at all cell sizes having values above 20. The curves also shift at about this point for all cell sizes, from a generally right-shift as cell size increases, to more of an upward shift; indicating a smaller number of the very highest values.

Figure 26: CFD for Plan Stream Power Index
Table 15: Results of the Kolmogorov-Smirnov Test on the Stream Power Index

<table>
<thead>
<tr>
<th>Stream Power Index</th>
<th>D Max</th>
<th>Occurred At</th>
<th>Total n</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 and 40</td>
<td>0.1453</td>
<td>0.7664566</td>
<td>5759502</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 80</td>
<td>0.3049</td>
<td>1.3066520</td>
<td>4897068</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 160</td>
<td>0.4615</td>
<td>1.9904480</td>
<td>4680470</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 320</td>
<td>0.5938</td>
<td>3.1079860</td>
<td>4626344</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 640</td>
<td>0.6743</td>
<td>4.0177690</td>
<td>4612825</td>
<td>0.001</td>
</tr>
</tbody>
</table>

An observation of the results of the D-Max statistic for the stream power index indicate a trend similar to that seen for the other terrain attributes, where the D-Max value increases as cell size does. At each cell size, the result of the difference is significant, meaning that the CFD of values is significantly different when computed from DEMs of increasingly coarse resolution.

4.1.7 Wetness Index

Figure 27 shows the variation in the computed wetness index across the transect at various cell sizes. Generally, the surface is modeled to be ‘wetter’ at larger cell sizes, and less prone to saturation at smaller cell sizes. The graph line from the 640 foot DEM is generally higher and much less variable than the graph line of the wetness index from smaller cell sizes. There is much more variability in the wetness index at the smaller cell sizes, but values are lower overall with most of the values along the transect being smaller at the small cell sizes that the same location represented by a larger cell size. This is consistent with the values observed in the descriptive statistics, where it was shown that the mean value of the wetness index increases at the watershed level as cell size does.
Figure 27: Wetness Index Variability along a Transect at Different Cell Sizes

Wetness index values vary quite strongly when computed from DEMs of increasingly coarse resolutions. There is a steady increase in both the mean and minimum values with larger cell sizes, as shown in Table 16. The minimum values range from 3.5 for the 20 foot DEM, to 9.96 for the 640 foot DEM. There is also a steady increase in mean values from 8.7 for the 20 foot DEM to 12.41 for the 640 foot DEM. Although the mean values do not reflect this increase directly, the maximum values behave in a different manner increasing steadily when computed from the 20 foot through the 160 foot DEM, and then falling slightly when computed from the 320 and 640 foot DEMs, to values seen at the finer resolutions. Generally though the wetness index values increase for the watershed with increasingly coarse resolutions, indicating the potential
for increased soil saturation, or the increased likelihood of prediction of saturation, when using coarse DEMs to compute the wetness index. The relationship for the wetness index values are shown graphically in Figure 28. Interestingly, the increase in minimum and mean wetness index values with an increase in cell size is nearly parallel, increasing most likely in a logarithmic fashion.

Table 16: Summary statistics for wetness index

<table>
<thead>
<tr>
<th>Cell Size (ft)</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Range</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>3.494</td>
<td>19.301</td>
<td>15.807</td>
<td>8.700970</td>
<td>1.511</td>
</tr>
<tr>
<td>40</td>
<td>5.088</td>
<td>21.774</td>
<td>16.687</td>
<td>9.264280</td>
<td>1.485</td>
</tr>
<tr>
<td>80</td>
<td>6.242</td>
<td>23.706</td>
<td>17.464</td>
<td>9.949130</td>
<td>1.573</td>
</tr>
<tr>
<td>160</td>
<td>7.402</td>
<td>24.246</td>
<td>16.845</td>
<td>10.629800</td>
<td>1.625</td>
</tr>
<tr>
<td>320</td>
<td>8.693</td>
<td>19.755</td>
<td>11.062</td>
<td>11.465500</td>
<td>1.607</td>
</tr>
</tbody>
</table>

Figure 28: Maximum, Minimum, and Mean Computed Wetness Index by Cell Size
In order to clearly show the trend of mean wetness index values, the mean wetness index values for each cell size are shown separately in Figure 29, along with a log-trend line, formula and $R^2$ value for the relationship.

![Mean Wetness Index Values for each Cell Size](image)

**Figure 29: Mean Computed Wetness Index by Cell Size with Log Trend Line**

Figure 29 shows a very strong log relationship between cell size and mean wetness index, as indicated through the very large $R^2$ value of 0.992. This logarithmic relationship is very similar to the form and strength as observed for slope in Figure 13.

The CFDs for the wetness index indicate a generally parallel shift to the right as cell sizes increase, as shown in Figure 30. These higher values indicate an increased potential or prediction of soil saturation. The potential for soil saturation increases as the cell size from which it is computed does. There are very few areas of very high wetness index, and no abrupt shifts in the distribution. Generally though, these distributions show
that the surface is predicted to be wetter when represented by DEMs with increasingly coarse resolutions.

![CFD for Wetness Index](image)

Figure 30: CFD for Wetness Index

<table>
<thead>
<tr>
<th>Wetness Index</th>
<th>D Max</th>
<th>Occurred At</th>
<th>Total n</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 and 40</td>
<td>0.1937</td>
<td>8.309067</td>
<td>5810087</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 80</td>
<td>0.4019</td>
<td>8.678735</td>
<td>4937846</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 160</td>
<td>0.5818</td>
<td>9.068766</td>
<td>4719673</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 320</td>
<td>0.7528</td>
<td>9.712436</td>
<td>4665152</td>
<td>0.001</td>
</tr>
<tr>
<td>20 and 640</td>
<td>0.8723</td>
<td>10.573270</td>
<td>4651520</td>
<td>0.001</td>
</tr>
</tbody>
</table>

The results for the wetness index parameter are comparable to that of the stream power index. While the shapes of the distribution are different, there is similarity in the way that the D-Max statistic increases as cell size does. When compared to the CFD for the 20 foot cell size, the distribution for each successive distribution is significantly different, and the D-Max statistic increases in value. This indicates an increase in the
difference between the distributions as cell size increases. For all terrain attributes except
elevation, the results indicate that there is a statistically significant difference between the
CFDs of values when computed from large DEM cell sizes, as compared to those
computed from the high resolution 20 foot DEM.
4.2 Stream Analysis

4.2.1 Stream Network Comparison

Figures 31 through 36 show a visual overall comparison of the stream networks as mapped through an orthophoto (Figure 31) and as derived from a DEM for successively coarse DEM resolutions (Figures 32 through 36).

Figure 31: Orthophoto Derived Stream Network
Figure 32: Streams Derived from 20 foot DEM
Figure 33: Streams Derived from 40 foot DEM
Figure 34: Streams Derived from 80 foot DEM
Figure 35: Streams Derived from 160 foot DEM
Some difference in the stream networks is apparent when viewed at a small scale, however, viewing the network at a large scale is necessary to observe the effect of DEM resolution upon the derivation of a stream networks from DEMs of increasingly coarse resolutions. Figures 37 to 42 below show, for a sample of the study area, how the stream network differs when derived from a DEM of increasingly coarse resolution, with the same contributing area threshold, as compared to a photogrammetrically mapped stream network. Figure 37 shows the streams derived from a 20 foot DEM compared to photogrammetrically mapped streams. Visually, the stream networks match very closely, with similar meanders, both following the valleys evident on the surface very well. There

Figure 36: Streams Derived from 320 foot DEM
is some difference in stream length. In some cases, the photogrammetrically mapped streams are slightly longer than the derived streams, and in other cases the derived streams are longer. When determining the contributing area threshold to use to initiate a stream network, one was chosen that resulted in a stream network that most closely resembled the mapped stream network in terms of the channel initiation points. This threshold was found by experimenting with a range of threshold values. The derived stream network, even from a high resolution DEM will not be consistent in all streams when a single stream initiation threshold is used.

Figure 37: Streams Derived from a 20 foot Cell Size and Photogrammetrically Mapped Streams
As the streams are derived from DEMs of coarser cell sizes, detail is lost in the stream network, as shown in Figure 38. This Figure shows the stream network derived from a 40 foot DEM, and the mapped stream network. Although similar in morphology to the mapped stream network, and the stream network derived from the 20 foot DEM, it is obvious that some detail is lost in the stream network.

![Figure 38: Streams Derived from a 40 foot Cell Size and Photogrammetrically Mapped Streams](image)

Figure 39 shows the relationship between the mapped stream network, and that derived from a DEM with a cell size of 80 feet. At this resolution, much detail in the stream network is lost. The streams generally follow the depressions in the DEM, and follow the general morphology of the mapped stream network. Although stream lengths
appear to be similar between the derived streams and the mapped streams, the fine detail in the network observed at higher resolutions is gone. There are many straight stream segments, which are very different than the mapped stream network. The network becomes more linear and straight at this resolution, resulting in only a vague representation of the natural stream network.

Figure 39: Streams Derived from a 80 foot Cell Size and Photogrammetrically Mapped Streams

The generalization of the stream network increases when derived from a 160 foot DEM, as compared to both the photogrammetrically mapped stream network, and those derived from higher resolution DEMs. As shown in Figure 40, the stream network only vaguely resembles the mapped stream network. The derived stream network consists of
straight segments with very little detail. Any fine meander or detail that is present in the mapped network is not present in the derived network, a function of the fact that the meander cannot be represented with such a large cell size, and of the generalization that would naturally occur in a stream network derived from such a coarse DEM. At this cell size, the derived network crosses through peaks in the surface where a stream would not be expected to flow, and is not representative of the natural stream network.

Figure 40: Streams Derived from a 160 foot Cell Size and Photogrammetrically Mapped Streams

The final cell size for which a stream network was derived is 320 feet. Streams were not derived from the 640 foot DEM, because at this cell size the initiation threshold area is less than the area of one cell at 640 feet. The result of the derivation is shown in
Figure 41. At this cell size, any detail that was present in the mapped stream network, or that derived from the high resolution DEM is lost. Streams are very general, and the lengths are very underestimated, as the streams are straight lines in the derived network, where they meander in nature. The derived stream network follows very generally the morphology of the mapped network, but because of the large cell size, the stream network is very far from its natural location. This is a function of the cell size used to derive the network; the natural network simply cannot be represented adequately at this cell size. Many small streams are not represented in this derived network either. Quite possibly, the natural streams that are not represented are shorter than the 320 foot cell size that they are being derived from.
Figure 41: Streams Derived from a 320 foot Cell Size and Photogrammetrically Mapped Streams

The final Figure in this series, Figure 42 shows all of the derived stream networks together with the photogrammetrically mapped streams. It is obvious that there is much difference between each of the derived networks and the photogrammetrically derived networks. The differences in the networks increase as the cell size from which they are derived does. At all cell sizes though, there are some small stream segments that are not represented in the derived network whatsoever. When derived from large cell sizes, the location of the stream networks tend to not represent the true location of the network, nor do they represent the true morphology of the natural stream network. Streams can only be located in very general terms when derived from DEMs with large cell sizes.
4.2.2 Stream Network Statistical Analysis

To evaluate the accuracy of the streams derived directly from a 20 foot DEM compared to streams mapped through photogrammetric methods, several techniques were used. The Kappa Index of Agreement (KIA) was used to investigate the stream agreement, by order, between these two stream datasets. To complete this task, the photogrammetrically mapped streams were ordered using the RivEx stream ordering tool, and then rasterized to a 20 foot cell size while being snapped to the 20 foot DEM so that the cells would be aligned in the same grid system as the DEM derived stream network.
The KIA is able to test for raster independence, and quantify the level of raster agreement.

Table 18 gives the cell count for the interception of all streams from the 20 foot DEM, irrespective of order. The overwhelming number of cells in each raster did not represent stream networks at all. Direct comparisons at this level are not useful, there are simply too many cells that are not streams overall. However, an examination of the KIA is useful for comparison, as the KIA corrects for chance, comparing the cell agreement against the agreement that might be expected as chance. For this reason, the KIA can be thought of as the chance-corrected proportion of agreement (Chuang, 2001).

Table 18: Cell Agreement Count Matrix for Boolean Stream Network

<table>
<thead>
<tr>
<th>Mapped Streams</th>
<th>Derived Streams</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>Total</td>
</tr>
<tr>
<td>Streams 0</td>
<td>17715936</td>
<td>129085</td>
<td>17845021</td>
</tr>
<tr>
<td></td>
<td>93325</td>
<td>61654</td>
<td>154979</td>
</tr>
<tr>
<td>Total</td>
<td>17809261</td>
<td>190739</td>
<td>18000000</td>
</tr>
</tbody>
</table>

Table 19 gives the raw cell agreement counts between the rasterized photogrammetrically mapped streams, and the streams derived from the 20 foot DEM, by order. The numbers from Tables 18 and 19 are then used to derive the KIA. The KIA for Tables 18 and 19 are both different, but both are meaningful. The values in Table 18 are a measure of agreement without considering order. The values in Table 19 are a measure of agreement considering order. The agreement values in Table 19 are used to determine the KIA for each order of stream. These values are also used to calculate a third value of the KIA, one that does not explicitly determine the KIA by order, but for the stream network as a whole considering order.
Table 19: Cell Agreement Count Matrix for 20' DEM Derived vs. Mapped Stream Network

<table>
<thead>
<tr>
<th>Mapped Stream Network</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Derived Stream Network</td>
<td>17715936</td>
<td>50696</td>
<td>20492</td>
<td>11117</td>
<td>4258</td>
<td>2910</td>
<td>151</td>
<td>17805560</td>
</tr>
<tr>
<td>Stream Network</td>
<td>1</td>
<td>71046</td>
<td>19416</td>
<td>2983</td>
<td>425</td>
<td>205</td>
<td>228</td>
<td>231</td>
</tr>
<tr>
<td>Network</td>
<td>3</td>
<td>14288</td>
<td>1207</td>
<td>4163</td>
<td>4822</td>
<td>729</td>
<td>81</td>
<td>172</td>
</tr>
<tr>
<td>Total</td>
<td>6</td>
<td>3221</td>
<td>80</td>
<td>65</td>
<td>24</td>
<td>1</td>
<td>2</td>
<td>1297</td>
</tr>
</tbody>
</table>

Table 20 gives the KIA for the photogrammetrically mapped streams and the streams derived from the 20 foot DEM. Results are given for the overall stream network irrespective of stream order, the overall stream network considering order, and for each stream order individually. Higher numbers for the KIA indicate a greater strength of agreement. Generally, the KIA results indicate a low level of agreement between the two stream networks. The agreement for the overall network at 0.35 is higher than any other value besides the sixth-order stream agreement. This seems likely, as the KIA in this case was based strictly on whether a cell was a stream in both rasters, not on whether the corresponding order was captured correctly. The low value of 0.238 for the first order network is expected as well. As observed previously, because the DEM derived streams are based on a contributing area threshold, the location of initiation of a first-order stream is often incorrect. Sometimes the point of initiation of a first-order stream in a DEM derived network will correspond directly with that of a “blue line” stream in a mapped network. Other times, the location for initiation of a first-order stream will be different, as shown in Figure 37. This low value for the KIA reflects this fact.
Figure 43: Result of Error in Initiating a First-Order Stream, Cascade Effect

Figure 43 shows the effect on stream order when a first-order stream is initiated in the wrong location. The two short stream segments in the inlaid box are classified as first-order streams when derived from the 20 foot DEM. However, these stream segments are not present in the mapped stream network. Instead, the second-order derived stream segment begins at approximately the same location as the first-order mapped stream. This effect will cascade down the stream network, misclassifying the downstream segments. As a comparison, the first-order streams in the lower right corner of Figure 43 show the initiation of the first-order derived stream as being very close to the initiation point of the mapped first-order stream.
It is logical that the KIA generally increases as the stream order value increases. While the location of initiation of a first-order stream is often incorrect, there is greater chance that the location of higher-order streams will agree. Visually, there is less variability in the stream networks as the stream order increases, and this is reflected in the KIA values in Table 20. The KIA for the overall network considering order is 0.289. This value is lower than the KIA value of 0.35 that was observed for the stream network not considering order, as expected. This again indicates that there is some misclassification of stream order. When the stream networks are considered as Boolean networks, there is more agreement, as there is no stream order classification to consider.

### Table 20: Kappa Index of Agreement for 20 foot DEM

<table>
<thead>
<tr>
<th>Kappa Index of Agreement (KIA) Statistic</th>
<th>Stream Location Agreement for 20’ DEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall KIA without considering order</td>
<td>0.350</td>
</tr>
<tr>
<td>Overall KIA with consideration of order</td>
<td>0.289</td>
</tr>
<tr>
<td>Individual KIA - First Order</td>
<td>0.238</td>
</tr>
<tr>
<td>Individual KIA - Second Order</td>
<td>0.232</td>
</tr>
<tr>
<td>Individual KIA - Third Order</td>
<td>0.274</td>
</tr>
<tr>
<td>Individual KIA - Fourth Order</td>
<td>0.288</td>
</tr>
<tr>
<td>Individual KIA - Fifth Order</td>
<td>0.313</td>
</tr>
<tr>
<td>Individual KIA - Sixth Order</td>
<td>0.434</td>
</tr>
</tbody>
</table>

#### 4.2.3 Comparison of Vector Stream Locations

To further investigate the agreement between the mapped stream network, and those derived from DEMs of varying resolutions, an analysis of the vector stream networks was completed. This involved buffering the mapped stream network by the
width of one pixel (20 feet) and intersecting the five different stream networks with this buffer. The result is an interception table that gives the percentage of the network intersected by the buffer for each cell size, and for each order. The results are presented in Table 21.

Table 21: Results of Intersection of Mapped Stream Buffer and Derived Stream Networks

<table>
<thead>
<tr>
<th>DEM Cell Size (ft)</th>
<th>20</th>
<th>40</th>
<th>80</th>
<th>160</th>
<th>320</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Interception</td>
<td>67.31%</td>
<td>65.54%</td>
<td>64.24%</td>
<td>60.06%</td>
<td>59.76%</td>
</tr>
<tr>
<td>First Order</td>
<td>32.75%</td>
<td>32.27%</td>
<td>32.15%</td>
<td>30.28%</td>
<td>30.11%</td>
</tr>
<tr>
<td>Second Order</td>
<td>28.94%</td>
<td>28.61%</td>
<td>29.54%</td>
<td>27.93%</td>
<td>27.64%</td>
</tr>
<tr>
<td>Third Order</td>
<td>22.75%</td>
<td>24.64%</td>
<td>23.12%</td>
<td>22.91%</td>
<td>26.71%</td>
</tr>
<tr>
<td>Fourth Order</td>
<td>22.59%</td>
<td>27.01%</td>
<td>20.73%</td>
<td>22.20%</td>
<td>20.94%</td>
</tr>
<tr>
<td>Fifth Order</td>
<td>33.03%</td>
<td>35.09%</td>
<td>29.96%</td>
<td>28.18%</td>
<td>29.02%</td>
</tr>
<tr>
<td>Sixth Order</td>
<td>42.83%</td>
<td>41.21%</td>
<td>37.00%</td>
<td>36.04%</td>
<td>29.04%</td>
</tr>
</tbody>
</table>

Overall, the length of the network intercepted declines steadily between the 20 foot and 320 foot cell sizes. The overall stream network is successfully intercepted 67.31% of its length, while this decreases to only 59.76% for the stream network generated with the 320 foot DEM. As is evident from these observations, a stream network more closely resembling the mapped network is derived from the higher resolution DEM.

The results of the network interception by order are not always consistent across all resolutions. For first-order streams, about 32% of the stream network is intercepted for all resolutions, falling to about 30% for the 160 and 320 foot steam networks. The results for second-order streams are similar. About 29% of the second-order stream network is intercepted for the 20, 40, and 80 foot DEMs, falling slightly by about 2% for the 160 and 320 foot cell sizes. For the third-order streams, although the percentage of the stream network intercepted is similar, between about 22% and 24% intercepted for the 20 to 160 foot cell size, the amount of interception is largest for the 320 foot cell size.
at about 26%. This contrasts the first and second-order stream networks that have their lowest interception values at the higher cell sizes. The results for the fourth-order streams are inconsistent. For the 20, 40, 80, 160, and 320 foot cell sizes respectively, the results are 22.59%, 27.01%, 20.73%, 22.2%, and 20.94%. These results show no clear trend, but the amount of interception is generally low. The results for fifth-order streams do not show a clear trend either. The greatest amount of interception is observed at with the 20 foot and 40 foot cell size stream networks, at about 33% and 35% respectively. This represents a large improvement in interception over the fourth-order networks, and a much higher level of interception than observed for the 80, 160, and 320 foot stream networks. For the sixth-order streams, the interception rate is generally much higher, a result consistent with the results of the KIA discussed earlier. Sixth-order streams generated from the 20 foot DEM were intercepted correctly almost 43% of the time. The results for the 40 foot stream network were similar with about a 41% interception rate. The rate of interception decreased steadily for the larger cell sizes though, to a low of only 29% for the 320 foot stream network. Generally, it appears that the higher resolution stream network more closely resembles the photogrammetrically mapped stream network. It is important to note however, that the overall interception is much better than the interception observed by order. A likely reason for this is the use of a constant stream initiation threshold used to initiate streams. First-order streams will often start in the incorrect place, resulting in the first-order derived streams linking up with second-order photogrammetrically mapped streams or vice-versa. This error will cascade down the rest of the stream orders as seen in Figure 43. As was observed with the KIA,
stream accuracy results are in part affected by stream length issues, and the location of initiation of first-order streams, second-order streams, etc.

### 4.2.4 Stream Morphology Statistics

In addition to reporting the level of stream agreement between the derived stream network and the photogrammetrically mapped stream network, the stream morphology characteristics provide a number of good metrics for comparison. The stream morphology statistics provide information about the stream network that is not apparent from an examination of the location of the stream networks alone. For instance, Table 22 gives the total count of the number of stream segments, by order, for each of the stream networks including the photogrammetrically mapped stream network from Wake County.

Results for the first-order stream networks reveal that there are many more first order streams in each of the derived networks other than the 320 foot network, than there is in the mapped stream network. For the 20 foot cell size, there are 968 more first order streams present than in the mapped stream network, a significant increase. In general terms, there is a steady decrease in the number of first order streams derived as the cell size increases. This increase could be partly due again to the choice of a constant contributing area threshold used to initiate a stream network from the DEM. Removal of short first-order streams from the derived stream network could result in the number of first-order streams being closer to those in the mapped network. As discussed previously, when a constant channel initiation threshold is used, the initiation point of a channel can often be incorrect, and streams that could be simply ephemeral streams or gullies could be incorrectly identified as first-order streams. “Pruning” these short first-order streams
from the network could reduce the possibility of this error. This consideration is more likely when the results for the second-order stream network counts are observed. Further, the channel initiation technique could be reconsidered, for instance a variable threshold could be used instead of a constant stream initiation threshold.

As expected, there are far fewer second-order streams at each cell size than there are first-order streams. However, the results are much more tightly grouped for the second order streams. For instance, there are 1280 second order stream segments in the 20 foot stream network, whereas there are 900 observed in the photogrammetrically mapped stream network for a difference of only 380. The number of second-order stream segments decrease steadily for each increased cell size, with the number of second-order streams being underestimated at the 320 foot cell size by 238 stream segments. The number of stream segments are underestimated by the 320 foot stream network for every order, except for the fourth-order, where the results are extremely close; within one stream segment of each other.

Overall, the numbers of stream segments in the derived networks tend to overestimate the actual number of segments at every order, with the exception of the 320 foot network, which underestimates. Also in general terms, as the cell size from which a stream network is derived increases, the trend is for the number of stream segments by order to decrease. By increasing the cell size that is used to derive a stream network, the detail in that network begins to decrease, perhaps making the stream network less reliable. Importantly, higher DEM resolution does not provide better estimates of stream segment counts; however the results are very dependent upon the channel initiation technique used.
Table 22: Count of Stream Segments by Order

<table>
<thead>
<tr>
<th>Cell Size (ft)</th>
<th>First Order</th>
<th>Second Order</th>
<th>Third Order</th>
<th>Fourth Order</th>
<th>Fifth Order</th>
<th>Sixth Order</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>2784</td>
<td>1280</td>
<td>779</td>
<td>329</td>
<td>218</td>
<td>156</td>
<td>5546</td>
</tr>
<tr>
<td>40</td>
<td>2722</td>
<td>1233</td>
<td>759</td>
<td>309</td>
<td>207</td>
<td>161</td>
<td>5391</td>
</tr>
<tr>
<td>80</td>
<td>2572</td>
<td>1172</td>
<td>628</td>
<td>306</td>
<td>215</td>
<td>159</td>
<td>5052</td>
</tr>
<tr>
<td>160</td>
<td>2645</td>
<td>1113</td>
<td>696</td>
<td>246</td>
<td>211</td>
<td>140</td>
<td>5051</td>
</tr>
<tr>
<td>320</td>
<td>1796</td>
<td>662</td>
<td>385</td>
<td>200</td>
<td>92</td>
<td>111</td>
<td>3246</td>
</tr>
<tr>
<td>Mapped Streams</td>
<td>1816</td>
<td>900</td>
<td>439</td>
<td>199</td>
<td>149</td>
<td>164</td>
<td>3667</td>
</tr>
</tbody>
</table>

The bifurcation ratio of a stream network gives the relationship between the number of streams in one order to the number of streams in the next successive order. In nature, bifurcation ratios of between 3 and 5 are common (Summerfield, 1991). Table 23 summarizes the bifurcation ratios computed for each derived stream network and the photogrammetrically mapped stream network. The results for the bifurcation ratios by order don't reveal consistent increases or decreases, but indicate a less reliable estimate of stream network properties. None of the derived stream networks represent the bifurcation ratios in the photogrammetrically mapped streams very well. Importantly, higher DEM resolution does not provide better estimates of the bifurcation ratios, much the same as was observed with raw stream segment counts. The results are very dependent however upon the channel initiation technique used.
Table 23: Bifurcation Ratios

<table>
<thead>
<tr>
<th>Cell Size (ft)</th>
<th>$R_{B1}$</th>
<th>$R_{B2}$</th>
<th>$R_{B3}$</th>
<th>$R_{B4}$</th>
<th>$R_{B5}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>2.18</td>
<td>1.64</td>
<td>2.37</td>
<td>1.51</td>
<td>1.40</td>
</tr>
<tr>
<td>40</td>
<td>2.21</td>
<td>1.62</td>
<td>2.46</td>
<td>1.49</td>
<td>1.29</td>
</tr>
<tr>
<td>80</td>
<td>2.19</td>
<td>1.87</td>
<td>2.05</td>
<td>1.42</td>
<td>1.35</td>
</tr>
<tr>
<td>160</td>
<td>2.38</td>
<td>1.60</td>
<td>2.83</td>
<td>1.17</td>
<td>1.51</td>
</tr>
<tr>
<td>320</td>
<td>2.71</td>
<td>1.72</td>
<td>1.93</td>
<td>2.17</td>
<td>0.83</td>
</tr>
<tr>
<td>Mapped Streams</td>
<td>2.02</td>
<td>2.05</td>
<td>2.21</td>
<td>1.34</td>
<td>0.91</td>
</tr>
</tbody>
</table>

Table 24 presents the actual length of streams in each order. As observed in the table, as DEM cell size increases, the overall stream length decreases. This trend applies to all stream orders except for first-order streams. Length of first-order streams remain roughly the same as cell size increases. These stream lengths are used to compute the stream length ratio which is another metric used to make comparisons of streams in one order to streams in another order. In this case, the total length of streams in one order was compared to the total length of streams in the next successive order. The results are presented in Table 25. The results for stream length ratios show fairly substantial changes with resolution, with a substantial decrease overall.

Table 24: Length of Streams by Order (in feet)

<table>
<thead>
<tr>
<th>Cell Size (ft)</th>
<th>First Order</th>
<th>Second Order</th>
<th>Third Order</th>
<th>Fourth Order</th>
<th>Fifth Order</th>
<th>Sixth Order</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>1572989</td>
<td>851686</td>
<td>427970</td>
<td>165051</td>
<td>95911</td>
<td>77950</td>
<td>3191557</td>
</tr>
<tr>
<td>40</td>
<td>1559209</td>
<td>806728</td>
<td>417413</td>
<td>150066</td>
<td>85718</td>
<td>78599</td>
<td>3097733</td>
</tr>
<tr>
<td>80</td>
<td>1580573</td>
<td>777858</td>
<td>346017</td>
<td>153285</td>
<td>92066</td>
<td>78343</td>
<td>3028143</td>
</tr>
<tr>
<td>160</td>
<td>1731869</td>
<td>709981</td>
<td>359460</td>
<td>123860</td>
<td>83998</td>
<td>70610</td>
<td>3079777</td>
</tr>
<tr>
<td>320</td>
<td>1618614</td>
<td>551407</td>
<td>263184</td>
<td>124641</td>
<td>54033</td>
<td>69062</td>
<td>2680942</td>
</tr>
<tr>
<td>Mapped Streams</td>
<td>1266056</td>
<td>606765</td>
<td>313032</td>
<td>125860</td>
<td>77837</td>
<td>93927</td>
<td>2483476</td>
</tr>
</tbody>
</table>
Table 25: Stream Length Ratios

<table>
<thead>
<tr>
<th>Cell Size (ft)</th>
<th>R_L1</th>
<th>R_L2</th>
<th>R_L3</th>
<th>R_L4</th>
<th>R_L5</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>0.54</td>
<td>0.50</td>
<td>0.39</td>
<td>0.58</td>
<td>0.81</td>
</tr>
<tr>
<td>40</td>
<td>0.52</td>
<td>0.52</td>
<td>0.36</td>
<td>0.57</td>
<td>0.92</td>
</tr>
<tr>
<td>80</td>
<td>0.49</td>
<td>0.44</td>
<td>0.44</td>
<td>0.60</td>
<td>0.85</td>
</tr>
<tr>
<td>160</td>
<td>0.41</td>
<td>0.51</td>
<td>0.34</td>
<td>0.68</td>
<td>0.84</td>
</tr>
<tr>
<td>320</td>
<td>0.34</td>
<td>0.48</td>
<td>0.47</td>
<td>0.43</td>
<td>1.28</td>
</tr>
<tr>
<td>Mapped Streams</td>
<td>0.48</td>
<td>0.52</td>
<td>0.40</td>
<td>0.62</td>
<td>1.21</td>
</tr>
</tbody>
</table>

The results in Table 25 indicate that higher resolution DEMs do not produce better estimates of stream length order, but the results are very sensitive to the channel initiation technique used to derive them.
Chapter 5
Conclusions

Beven and Moore (1992) noted that digital terrain modeling is not new in the field of hydrology, and in fact the characterization of the topography must be important in hydrology. However, what is different now is that the era of GIS, simulation visualization software, and workstation computing power has arrived and is rapidly maturing. New, higher resolution elevation data from new collection methods and sensors such as LIDAR has provided the opportunity to explore hydrologic and other physical processes at scales not previously explored. It also raises a question as to the advantage (if any) of high resolution elevation data in the study of hydrologic and terrain processes. It is often preferable to allow necessity to drive technology, rather than have technology influence our needs. Are high resolution elevation data sets a case where technology has led the change?

This thesis research had one goal; to determine the effect of DEM resolution upon hydrologically significant terrain attributes, including stream networks. It proposed to determine this effect through two objectives. The first objective was to determine the effect of DEM resolution on hydrologically significant terrain derivatives including slope, plan curvature, profile curvature, overall curvature, topographic wetness index, and the stream power index. The second objective was to determine how the resolution of a DEM affects the morphology and attributes of the streams derived from it. Measures to
investigate this include the Kappa Index of Agreement (KIA), the length of derived streams intercepted by a buffered photogrammetrically mapped stream network, and the comparison of several morphological characteristics of the derived stream network, to that of the photogrammetrically mapped stream network.

To facilitate this research, a high resolution DEM data set derived from LIDAR data was acquired for a small North Carolina watershed. This DEM was resampled to successively coarser resolutions resulting in DEMs with 20, 40, 80, 160, 320, and 640 foot cell sizes. Terrain attributes with significance to hydrology and hydrologic modeling were then computed and compared between the resolutions.

DEM cell size was observed to have a significant effect upon the value of the computed attributes. As hypothesized, as the cell size from which slope was computed increased, the computed value of slope decreased. The amount of decrease was large; a maximum slope of 56.9 degrees was observed in the watershed when represented by a 20 foot DEM, while the maximum slope fell to only 5.3 degrees when represented by a 640 foot DEM. The mean slope values fell progressively as well, following a logarithmic curve. A logarithmic trend line added to the chart of mean slope graphed with DEM cell size resulted in a $R^2$ value of 0.9731. Slope has implications for overland and subsurface flow velocity and runoff rate and affects precipitation infiltration, among other surface processes.

Values for overall, plan, and profile surface curvature were hypothesized to become limited in their spread, and the mean values of the curvature attributes were expected to decrease with an increase in cell size from which they are computed. This phenomenon was observed though examination of the summary statistics and cumulative
frequency diagrams for the attribute. Generally, when computed from a DEM of 80 foot cell size or greater, there is very little curvature represented in the surface and the results have little meaning for terrain analysis or hydrologic modeling. The curvature attribute has implications for flow acceleration, the erosion and deposition rate, converging and diverging flow, soil water content, and soil characteristics.

The stream power index and the topographic wetness index were topographic attributes included in the research for a number of reasons. These included the fact that they are both compound terrain attributes, encompassing a first derivative attribute, and because of their importance to hydrology and hydrologic modeling. The stream power index was hypothesized to increase as cell size increased, as this attribute will increase in proportion to an increase in the specific catchment area, which increases with an increase in DEM cell size used to derive it. The stream power index increased steadily with an increase in cell size, from a value of 7.25 from a 20 foot cell size to a high of 29.8 when computed from a 604 foot cell size DEM. This attribute has importance to hydrology, as it is able to predict areas of net erosion and net deposition when combined with a curvature parameter indicating areas of flow acceleration or deceleration.

As previous studies (Zhang and Montgomery, 1994) have concluded and as was hypothesized in this research, the topographic wetness index increases in value, and causes a surface to be modeled as ‘wetter’ when computed from DEMs of increasing resolution. The topographic wetness index describes the spatial distribution and extent of zones of for runoff generation as a function of upslope contributing area, soil transmissivity, and slope. It is also a key component of the TOPMODEL (Beven and Kirkby, 1979) hydrologic modeling framework.
The second objective of this research was to determine the effect of DEM resolution on the stream networks derived from DEMs. To test this, streams were delineated using the same contributing area threshold from a DEM with cell sizes of 20, 40, 80, 160, and 320 feet. These were then compared to a photogrammetrically mapped stream network. Visual and quantitative comparisons of resulting stream locations were completed, and certain morphological attributes were compared to determine stream agreement.

The Kappa Index of Agreement (KIA) was also used to determine the amount of agreement for the 20 foot stream network. Agreement values were generally low with an overall agreement of 0.35, and values by order ranging from 0.23 to 0.43. The accuracy of each derived stream network was determined by comparing it to the photogrammetrically mapped stream network. The accuracy of the stream network was expected to decrease when derived from DEMs with large cell sizes. This was confirmed through an observation of the percentage of the stream network intercepted by the buffered photogrammetrically mapped stream network. Interception rates generally fell overall and by stream order when derived from DEMs of increasingly coarse resolutions. Overall interception was 67.3% for the 20 foot stream network, falling to only a 59.8% interception rate for the 320 foot stream network.

In addition to stream location agreement, stream morphology metrics were investigated. Bifurcation ratios were calculated for each of the derived stream networks and the photogrammetrically mapped stream network. The bifurcation ratios were not expected to decrease between one stream order and the next successive one as the cell size increased, but remain fairly constant. The results for the bifurcation ratios by order
don't reveal consistent increases or decreases, but indicate a less reliable estimate of stream network properties. None of the derived stream networks represent the bifurcation ratios in the photogrammetrically mapped streams very well.

For all stream orders other than first-order streams, as hypothesized, the stream length decreased as cell size used to derive the stream increased. This indicates less meander in the stream and a straightening of the stream network. This was also confirmed through a visual inspection of the stream network derived at each resolution. First-order stream length can be somewhat misleading, as the length of a first-order stream will change with the channel initiation technique used to initiate it, making these lengths often incorrect.

This research indicates that stream networks derived from larger cell size DEMs are less reliable than when derived from high-resolution DEMs. Through the observation of stream morphology and accuracy characteristics, it is noted that stream networks derived from high-resolution DEMs are able to more closely reflect a natural stream network. Derived stream networks more closely reflect the mapped natural stream network as stream-order increases. This was observed through the values of the stream interception analysis, with derived sixth-order streams matching the natural network the closest. The same results were obtained through the KIA. The derived sixth-order streams showed the most agreement with the mapped natural stream network.

The physical location of derived streams becomes less accurate when derived from DEMs with increasingly coarse resolutions, but there is little difference in the overall stream network statistics. For example, meandering is represented poorly using coarse DEMs, but this is true across all orders. For this reason, metrics like the
bifurcation ratio are not necessarily less accurate when computed from low resolution DEMs as compared to high resolution DEMs. These results indicate that when available, a high-resolution DEM would be preferable for stream network modeling.

Clearly, it is difficult to reliably derive the location of initiation of a first-order stream. This is further complicated by the use of a constant contributing area threshold across a whole watershed to determine the beginning of the stream network. This was a major reason why the stream networks derived from the LIDAR DEMs were not closer to the mapped streams. The correct length and count of first-order streams is difficult to determine, and most likely often incorrect.

There are many factors that can influence the values of terrain attributes computed from DEMs. Of these, cell size is only one factor. LIDAR data collection specifications, interpolation techniques, filtering techniques, flow routing algorithm, contributing area threshold, and error are a number of factors. All of these factors need to be considered when interpreting topographic attributes derived from DEMs and subsequently using the results to model hydrological processes.

Sensor technology continues to improve, and computing power continues to allow the mass consumption of very large, high resolution data sets. Based on the results of this research, using the highest resolution elevation data available is beneficial to terrain analysis and stream network analysis. Technology might be pushing the possibilities forward, but it is up to the terrain analyst or hydrologist to quantify and discover the benefit of these new data sources for their area of interest. Perhaps the ultimate goal of this research is to establish relationships that quantify the effects of DEM resolution upon hydrologically relevant terrain derivatives, which can then be considered when
processing DEMs from various resolutions for the purpose of parameterizing hydrologic models.

The future of this research could include using a DEM with even higher resolution. Now emerging are even higher resolution LIDAR data, including data with a cell size of less than 10 feet. Terrestrial based LIDAR sensors are bound to decrease the cost of LIDAR elevation acquisition and increase the availability and use of LIDAR derived elevation data sets.

Using alternatives to the contributing area threshold to initiate streams is a research opportunity provided by LIDAR DEMs. As observed, the channel initiation technique used to initiate a stream network can have a profound impact on the results of subsequent analysis, especially in terms of stream network morphology. By developing more adaptive techniques that are more flexible in terms on stream initiation, perhaps more accurate stream networks can be derived from DEMs where there is no mapped stream network, and more reliable stream morphology statistics can be generated.

The development of empirical relationships to describe the scale-dependency of terrain attributes is a future direction of this research. The results of this study indicate that empirical relationships can be derived between DEM cell size and the values of terrain attributes derived from DEMs. What is necessary to carry this work further is to research different locations at different scales to confirm what these relationships look like. This research could be conducted across a wide range of terrain types, i.e. coastal, plains, low, moderate, and high relief areas and locations representing areas of net erosion like the Appalachian Mountains, and areas of net deposition, like coastal Florida. Instead of a single watershed, a number of watersheds with different relief and area could
be compared. While this research was conducted within a sixth-order watershed, would the same results be observed in a watershed of greater order?

Further, resolution independent terrain derivatives need to be developed. There are few, if any, of these developed at the present time. Much research effort has been directed at quantifying the effect of DEM cell size upon terrain derivatives. The body of knowledge surrounding this is increasing rapidly, especially in this era of higher resolution data and increased computing power. Developing resolution independent metrics and derivatives is a logical next step in this process.
References Cited

Adler, D. 2001. IBM® DB2® Spatial Extender – Spatial data within the RDBMS. In *Proceedings of the 27th VLDB Conference, Roma, Italy*.


Appendix A: Geoprocessing Scripts

Python script used to create the flow direction and flow accumulation rasters
# *---------------------------------------------------------------------------
# Create_fdr_and_fac_Rasters.py
# *---------------------------------------------------------------------------

# Import system modules
import sys, string, os, win32com.client

# Create the Geoprocessor object
gp = win32com.client.Dispatch("esriGeoprocessing.GpDispatch.1")

# Check out any necessary licenses
gp.CheckOutExtension("spatial")

# Load required toolboxes...
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Spatial Analyst Tools.tbx")

# Local variables...
fdr640 = "D:\ThesisDataFolder_Streams\fdr640"
Output_drop_raster = ""
fdr320 = "D:\ThesisDataFolder_Streams\fdr320"
Output_drop_raster__2_ = ""
fdr160 = "D:\ThesisDataFolder_Streams\fdr160"
Output_drop_raster__3_ = ""
fdr80 = "D:\ThesisDataFolder_Streams\fdr80"
Output_drop_raster__4_ = ""
fdr40 = "D:\ThesisDataFolder_Streams\fdr40"
Output_drop_raster__5_ = ""
filldem40 = "D:\ThesisDataFolder_Streams\filldem40"
filldem80 = "D:\ThesisDataFolder_Streams\filldem80"
filldem160 = "D:\ThesisDataFolder_Streams\filldem160"
filldem320 = "D:\ThesisDataFolder_Streams\filldem320"
filldem640 = "D:\ThesisDataFolder_Streams\filldem640"
fac40 = "D:\ThesisDataFolder_Streams\fac40"
fac80 = "D:\ThesisDataFolder_Streams\fac80"
fac160 = "D:\ThesisDataFolder_Streams\fac160"
Appendix A (continued)

fac320 = "D:\ThesisDataFolder_Streams\fac320"
fac640 = "D:\ThesisDataFolder_Streams\fac640"

# Process: Flow Direction...
gp.FlowDirection_sa(filldem640, fdr640, "NORMAL", Output_drop_raster)

# Process: Flow Direction (2)...
gp.FlowDirection_sa(filldem320, fdr320, "NORMAL", Output_drop_raster__2__)

# Process: Flow Direction (3)...
gp.FlowDirection_sa(filldem160, fdr160, "NORMAL", Output_drop_raster__3__)

# Process: Flow Direction (4)...
gp.FlowDirection_sa(filldem80, fdr80, "NORMAL", Output_drop_raster__4__)

# Process: Flow Direction (5)...
gp.FlowDirection_sa(filldem40, fdr40, "NORMAL", Output_drop_raster__5__)

# Process: Flow Accumulation...
gp.FlowAccumulation_sa(fdr40, fac40, ""

# Process: Flow Accumulation (2)...
gp.FlowAccumulation_sa(fdr80, fac80, ""

# Process: Flow Accumulation (3)...
gp.FlowAccumulation_sa(fdr160, fac160, ""

# Process: Flow Accumulation (4)...
gp.FlowAccumulation_sa(fdr320, fac320, ""

# Process: Flow Accumulation (5)...
gp.FlowAccumulation_sa(fdr640, fac640, ""
Appendix A (continued)

Python script used to import topographic wetness index and stream power index ASCII files from the Terrain Analysis System to ArcGIS

# Import system modules
import sys, string, os, win32com.client

# Create the Geoprocessor object
gp = win32com.client.Dispatch("esriGeoprocessing.GpDispatch.1")

# Load required toolboxes...
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Conversion Tools.tbx")

# Local variables...
WI640 = "D:\ThesisDataFolder_Derivatives\wi640"
RSP640 = "D:\ThesisDataFolder_Derivatives\rsp640"
WI320 = "D:\ThesisDataFolder_Derivatives\wi320"
RSP320 = "D:\ThesisDataFolder_Derivatives\rsp320"
WI160 = "D:\ThesisDataFolder_Derivatives\wi160"
RSP160 = "D:\ThesisDataFolder_Derivatives\rsp160"
WI80 = "D:\ThesisDataFolder_Derivatives\wi80"
RSP80 = "D:\ThesisDataFolder_Derivatives\rsp80"
WI40 = "D:\ThesisDataFolder_Derivatives\wi40"
RSP40 = "D:\ThesisDataFolder_Derivatives\rsp40"
WI20 = "D:\ThesisDataFolder_Derivatives\wi20"
RSP20 = "D:\ThesisDataFolder_Derivatives\rsp20"
lidar20asc_RSP_asc = "D:\ThesisDataFolder_Derivatives\TAS\lidar20asc_RSP.asc"
lidar20asc_WI_asc = "D:\ThesisDataFolder_Derivatives\TAS\lidar20asc_WI.asc"
lidar40asc_RSP_asc = "D:\ThesisDataFolder_Derivatives\TAS\lidar40asc_RSP.asc"
lidar40asc_WI_asc = "D:\ThesisDataFolder_Derivatives\TAS\lidar40asc_WI.asc"
lidar80asc_RSP_asc = "D:\ThesisDataFolder_Derivatives\TAS\lidar80asc_RSP.asc"
lidar80asc_WI_asc = "D:\ThesisDataFolder_Derivatives\TAS\lidar80asc_WI.asc"
lidar160asc_RSP_asc = "D:\ThesisDataFolder_Derivatives\TAS\lidar160asc_RSP.asc"
lidar160asc_WI_asc = "D:\ThesisDataFolder_Derivatives\TAS\lidar160asc_WI.asc"
lidar320asc_RSP_asc = "D:\ThesisDataFolder_Derivatives\TAS\lidar320asc_RSP.asc"
lidar320asc_WI_asc = "D:\ThesisDataFolder_Derivatives\TAS\lidar320asc_WI.asc"
lidar640asc_RSP_asc = "D:\ThesisDataFolder_Derivatives\TAS\lidar640asc_RSP.asc"
lidar640asc_WI_asc = "D:\ThesisDataFolder_Derivatives\TAS\lidar640asc_WI.asc"
Appendix A (continued)

# Process: ASCII to Raster...

gp.ASCIIToRaster_conversion(lidar640asc_WI_asc, WI640, "FLOAT")

# Process: ASCII to Raster (2)...

gp.ASCIIToRaster_conversion(lidar640asc_RSP_asc, RSP640, "FLOAT")

# Process: ASCII to Raster (3)...

gp.ASCIIToRaster_conversion(lidar320asc_WI_asc, WI320, "FLOAT")

# Process: ASCII to Raster (4)...

gp.ASCIIToRaster_conversion(lidar320asc_RSP_asc, RSP320, "FLOAT")

# Process: ASCII to Raster (5)...

gp.ASCIIToRaster_conversion(lidar160asc_WI_asc, WI160, "FLOAT")

# Process: ASCII to Raster (6)...

gp.ASCIIToRaster_conversion(lidar160asc_RSP_asc, RSP160, "FLOAT")

# Process: ASCII to Raster (7)...

gp.ASCIIToRaster_conversion(lidar80asc_WI_asc, WI80, "FLOAT")

# Process: ASCII to Raster (8)...

gp.ASCIIToRaster_conversion(lidar80asc_RSP_asc, RSP80, "FLOAT")

# Process: ASCII to Raster (9)...

gp.ASCIIToRaster_conversion(lidar40asc_WI_asc, WI40, "FLOAT")

# Process: ASCII to Raster (10)...

gp.ASCIIToRaster_conversion(lidar40asc_RSP_asc, RSP40, "FLOAT")

# Process: ASCII to Raster (11)...

gp.ASCIIToRaster_conversion(lidar20asc_WI_asc, WI20, "FLOAT")

# Process: ASCII to Raster (12)...

gp.ASCIIToRaster_conversion(lidar20asc_RSP_asc, RSP20, "FLOAT")
Appendix A (continued)

Python script used to resample the original LIDAR DEM and generate the topographic attributes of slope, and the three curvature attributes, and convert the results to ASCII format for subsequent import to the Terrain Analysis System

# Model_Resample_Gen_Derivatives.py
# ---------------------------------------------------------------------------

# Import system modules
import sys, string, os, win32com.client

# Create the Geoprocessor object
gp = win32com.client.Dispatch("esriGeoprocessing.GpDispatch.1")

# Check out any necessary licenses
gp.CheckOutExtension("spatial")

# Load required toolboxes...
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Spatial Analyst Tools.tbx")
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Conversion Tools.tbx")
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Data Management Tools.tbx")

# Local variables...
lidar640ras = "D:\ThesisDataFolder_Derivatives\lidar640ras"
lidar_20_fl = "lidar_20_fl"
lidar40ras = "D:\ThesisDataFolder_Derivatives\lidar40ras"
lidar320ras = "D:\ThesisDataFolder_Derivatives\lidar320ras"
lidar80ras = "D:\ThesisDataFolder_Derivatives\lidar80ras"
lidar160ras = "D:\ThesisDataFolder_Derivatives\lidar160ras"
slope40 = "D:\ThesisDataFolder_Derivatives\slope40"
slope80 = "D:\ThesisDataFolder_Derivatives\slope80"
slope160 = "D:\ThesisDataFolder_Derivatives\slope160"
slope320 = "D:\ThesisDataFolder_Derivatives\slope320"
slope640 = "D:\ThesisDataFolder_Derivatives\slope640"
Slope20 = "D:\ThesisDataFolder_Derivatives\slope20"
curvature640 = "D:\ThesisDataFolder_Derivatives\curvature640"
profile640 = "D:\ThesisDataFolder_Derivatives\profile640"
plan640 = "D:\ThesisDataFolder_Derivatives\plan640"
curvature320 = "D:\ThesisDataFolder_Derivatives\curvature320"
profile320 = "D:\ThesisDataFolder_Derivatives\profile320"
Appendix A (continued)

plan320 = "D:\\ThesisDataFolder_Derivatives\\plan320"
curvature160 = "D:\\ThesisDataFolder_Derivatives\\curvature160"
profile160 = "D:\\ThesisDataFolder_Derivatives\\profile160"
plan160 = "D:\\ThesisDataFolder_Derivatives\\plan160"
curvature20 = "D:\\ThesisDataFolder_Derivatives\\curvature20"
profile20 = "D:\\ThesisDataFolder_Derivatives\\profile20"
plan20 = "D:\\ThesisDataFolder_Derivatives\\plan20"
curvature40 = "D:\\ThesisDataFolder_Derivatives\\curvature40"
profile40 = "D:\\ThesisDataFolder_Derivatives\\profile40"
plan40 = "D:\\ThesisDataFolder_Derivatives\\plan40"
curvature80 = "D:\\ThesisDataFolder_Derivatives\\curvature80"
profile80 = "D:\\ThesisDataFolder_Derivatives\\profile80"
plan80 = "D:\\ThesisDataFolder_Derivatives\\plan80"
slope40asc_asc = "D:\\ThesisDataFolder_Derivatives\\slope40asc.asc"
profile40asc_asc = "D:\\ThesisDataFolder_Derivatives\\profile40asc.asc"
plan40asc_asc = "D:\\ThesisDataFolder_Derivatives\\plan40asc.asc"
curvature40asc_asc = "D:\\ThesisDataFolder_Derivatives\\curvature40asc.asc"
slope80asc_asc = "D:\\ThesisDataFolder_Derivatives\\slope80asc.asc"
profile80asc_asc = "D:\\ThesisDataFolder_Derivatives\\profile80asc.asc"
plan80asc_asc = "D:\\ThesisDataFolder_Derivatives\\plan80asc.asc"
curvature80asc_asc = "D:\\ThesisDataFolder_Derivatives\\curvature80asc.asc"
slope20asc_asc = "D:\\ThesisDataFolder_Derivatives\\slope20asc.asc"
profile20asc_asc = "D:\\ThesisDataFolder_Derivatives\\profile20asc.asc"
plan20asc_asc = "D:\\ThesisDataFolder_Derivatives\\plan20asc.asc"
curvature20asc_asc = "D:\\ThesisDataFolder_Derivatives\\curvature20asc.asc"
slope160asc_asc = "D:\\ThesisDataFolder_Derivatives\\slope160asc.asc"
profile160asc_asc = "D:\\ThesisDataFolder_Derivatives\\profile160asc.asc"
plan160asc_asc = "D:\\ThesisDataFolder_Derivatives\\plan160asc.asc"
curvature160asc_asc = "D:\\ThesisDataFolder_Derivatives\\curvature160asc.asc"
slope320asc_asc = "D:\\ThesisDataFolder_Derivatives\\slope320asc.asc"
profile320asc_asc = "D:\\ThesisDataFolder_Derivatives\\profile320asc.asc"
plan320asc_asc = "D:\\ThesisDataFolder_Derivatives\\plan320asc.asc"
curvature320asc_asc = "D:\\ThesisDataFolder_Derivatives\\curvature320asc.asc"
slope640asc_asc = "D:\\ThesisDataFolder_Derivatives\\slope640asc.asc"
profile640asc_asc = "D:\\ThesisDataFolder_Derivatives\\profile640asc.asc"
plan640asc_asc = "D:\\ThesisDataFolder_Derivatives\\plan640asc.asc"
curvature640asc_asc = "D:\\ThesisDataFolder_Derivatives\\curvature640asc.asc"
lidar20asc_asc = "D:\\ThesisDataFolder_Derivatives\\lidar20asc.asc"
lidar80asc_asc = "D:\\ThesisDataFolder_Derivatives\\lidar80asc.asc"
lidar40asc_asc = "D:\\ThesisDataFolder_Derivatives\\lidar40asc.asc"
lidar640asc_asc = "D:\\ThesisDataFolder_Derivatives\\lidar640asc.asc"
lidar320asc_asc = "D:\\ThesisDataFolder_Derivatives\\lidar320asc.asc"
lidar160asc_asc = "D:\\ThesisDataFolder_Derivatives\\lidar160asc.asc"
# Process: Resample (2)...

tempEnvironment0 = gp.workspace
gp.workspace = "D:\ThesisDataFolder_Derivatives"
gp.Resample_management(lidar_20_fl, lidar40ras, "40", "NEAREST")
gp.workspace = tempEnvironment0

# Process: Slope 40...
gp.Slope_sa(lidar40ras, slope40, "DEGREE", "1")

# Process: Raster to ASCII...
gp.RasterToASCII_conversion(slope40, slope40asc_asc)

# Process: Curvature_40...
gp.Curvature_sa(lidar40ras, curvature40, "1", profile40, plan40)

# Process: Raster to ASCII (2)...
gp.RasterToASCII_conversion(profile40, profile40asc_asc)

# Process: Raster to ASCII (3)...
gp.RasterToASCII_conversion(plan40, plan40asc_asc)

# Process: Raster to ASCII (4)...
gp.RasterToASCII_conversion(curvature40, curvature40asc_asc)

# Process: Resample (4)...
gp.Resample_management(lidar_20_fl, lidar80ras, "80", "NEAREST")

# Process: Slope 80...
gp.Slope_sa(lidar80ras, slope80, "DEGREE", "1")

# Process: Raster to ASCII (5)...
gp.RasterToASCII_conversion(slope80, slope80asc_asc)

# Process: Curvature_80...
gp.Curvature_sa(lidar80ras, curvature80, "1", profile80, plan80)

# Process: Raster to ASCII (6)...
gp.RasterToASCII_conversion(profile80, profile80asc_asc)

# Process: Raster to ASCII (7)...
gp.RasterToASCII_conversion(plan80, plan80asc_asc)
Appendix A (continued)

# Process: Raster to ASCII (8)...
gp.RasterToASCII_conversion(curvature80, curvature80asc_asc)

# Process: Slope 20...
gp.Slope_sa(lidar_20_fl, Slope20, "DEGREE", "1")

# Process: Raster to ASCII (9)...
gp.RasterToASCII_conversion(Slope20, slope20asc_asc)

# Process: Curvature_20...
gp.Curvature_sa(lidar_20_fl, curvature20, "1", profile20, plan20)

# Process: Raster to ASCII (10)...
gp.RasterToASCII_conversion(profile20, profile20asc_asc)

# Process: Raster to ASCII (11)...
gp.RasterToASCII_conversion(plan20, plan20asc_asc)

# Process: Raster to ASCII (12)...
gp.RasterToASCII_conversion(curvature20, curvature20asc_asc)

# Process: Resample (5)...
gp.Resample_management(lidar_20_fl, lidar160ras, "160", "NEAREST")

# Process: Slope 180...
gp.Slope_sa(lidar160ras, slope160, "DEGREE", "1")

# Process: Raster to ASCII (13)...
gp.RasterToASCII_conversion(slope160, slope160asc_asc)

# Process: Curvature_160...
gp.Curvature_sa(lidar160ras, curvature160, "1", profile160, plan160)

# Process: Raster to ASCII (14)...
gp.RasterToASCII_conversion(profile160, profile160asc_asc)

# Process: Raster to ASCII (15)...
gp.RasterToASCII_conversion(plan160, plan160asc_asc)

# Process: Raster to ASCII (16)...
gp.RasterToASCII_conversion(curvature160, curvature160asc_asc)

# Process: Resample (3)...

133
gp.Resample_management(lidar_20_fl, lidar320ras, "320", "NEAREST")

# Process: Slope 320...
gp.Slope_sa(lidar320ras, slope320, "DEGREE", "1")

# Process: Raster to ASCII (17)...
gp.RasterToASCII_conversion(slope320, slope320asc_asc)

# Process: Curvature_320...
gp.Curvature_sa(lidar320ras, curvature320, "1", profile320, plan320)

# Process: Raster to ASCII (18)...
gp.RasterToASCII_conversion(profile320, profile320asc_asc)

# Process: Raster to ASCII (19)...
gp.RasterToASCII_conversion(plan320, plan320asc_asc)

# Process: Raster to ASCII (20)...
gp.RasterToASCII_conversion(curvature320, curvature320asc_asc)

# Process: Raster to ASCII (21)...
gp.Resample_management(lidar_20_fl, lidar640ras, "640", "NEAREST")

# Process: Slope 640...
gp.Slope_sa(lidar640ras, slope640, "DEGREE", "1")

# Process: Raster to ASCII (21)...
gp.RasterToASCII_conversion(slope640, slope640asc_asc)

# Process: Curvature_640...
gp.Curvature_sa(lidar640ras, curvature640, "1", profile640, plan640)

# Process: Raster to ASCII (22)...
gp.RasterToASCII_conversion(profile640, profile640asc_asc)

# Process: Raster to ASCII (23)...
gp.RasterToASCII_conversion(plan640, plan640asc_asc)

# Process: Raster to ASCII (24)...
gp.RasterToASCII_conversion(curvature640, curvature640asc_asc)

# Process: Raster to ASCII (25)...
gp.RasterToASCII_conversion(lidar_20_fl, lidar20asc_asc)
Appendix A (continued)

# Process: Raster to ASCII (26)...
gp.RasterToASCII_conversion(lidar80ras, lidar80asc_asc)

# Process: Raster to ASCII (27)...
gp.RasterToASCII_conversion(lidar40ras, lidar40asc_asc)

# Process: Raster to ASCII (28)...
gp.RasterToASCII_conversion(lidar640ras, lidar640asc_asc)

# Process: Raster to ASCII (29)...
gp.RasterToASCII_conversion(lidar320ras, lidar320asc_asc)

# Process: Raster to ASCII (30)...
gp.RasterToASCII_conversion(lidar160ras, lidar160asc_asc)