Evaluating the Effects of DEM Properties on the Spatial and Statistical Distribution of Hydrological Surface Attributes

by

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ABSTRACT

EVALUATING THE EFFECTS OF DEM PROPERTIES ON THE SPATIAL AND STATISTICAL DISTRIBUTION OF HYDROLOGICAL SURFACE ATTRIBUTES

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Incorporating topographic detail within advanced hydrological models has been achieved using digital elevation models (DEMs). Although DEMs prove useful for a number of hydrological applications, they are often the end result of numerous processing steps that contain some amount of uncertainty. These uncertainties greatly influence DEM quality and can further propagate to DEM-derived attributes. This research examines the impacts of DEM grid resolution, elevation source data, and conditioning techniques on the spatial and statistical distribution of field-scale hydrological attributes. Variation in DEM grid resolution and elevation source data resulted in significant differences in the spatial and statistical distributions of variables. The resulting effects of applied conditioning techniques were closely linked to DEM grid resolution; differences in derived attributes among conditioning techniques significantly increased with grid resolution. Greater consideration of DEM conditioning is therefore required at finer-resolutions.
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Chapter 1.0 Introduction

1.1 Background

Topography directly influences the spatial distribution of surface and near-surface water flow pathways. Variations in surface relief impact runoff and determine subsequent water drainage networks (Quinn et al., 1991). Incorporating topographic information within advanced hydrological models has been achieved using digital elevation models (DEM) (e.g. Walker and Willgoose, 1999; Zhang and Montgomery, 1994). DEMs digitally portray the spatial distribution of land surface elevations above a chosen datum. They have proved especially useful for a number of hydrological applications including stream network extraction (O’Callaghan and Mark, 1984; Tarboton, 1997; Freeman, 1991) and watershed delineation (Jenson, 1991; Jenson and Domingue, 1988; Erskine et al., 2006).

DEM are the end result of numerous data collection, interpolation, and processing steps. The progression from an actual land surface to a digital visualization of its topography requires a number of procedures that contain some amount of uncertainty (Bater and Coops, 2009). The inherent uncertainties associated with each DEM development stage can influence DEM quality and propagate to DEM-derived products (Fisher and Tate, 2006; Lindsay, 2006). DEM quality is commonly linked to three critical factors: [1] elevation source data, [2] DEM interpolation, and [3] DEM grid resolution (Walker and Willgoose, 1999; Lindsay and Creed, 2005). Numerous studies have explored the effects of elevation data, interpolation techniques, and grid resolution on the extraction and distribution of hydrological DEM surface derivatives (e.g. Walker and Willgoose, 1999; Garbrecht and Martz, 2000; Zhang and Montgomery, 1994; Lindsay and Creed, 2005; Aguilar et al., 2005; Wolock and Price, 1994; McMaster, 2002; Clarke and Archer, 2009).
DEM accuracies that are used for hydrological applications are particularly sensitive to the various sources of error that affect DEM production, since even small, localized elevation errors can result in significant diversion or interruption of surface flowpaths. DEM error often manifests in the form of topographic depressions, defined as a single grid cell or group of neighboring grid cells that are not linked to a downslope outlet or flowpath (Jenson and Domingue, 1988). In fact, depressions within DEMs are often a combination of actual topographic depressions and artificial depressions caused by various data collection and processing errors (Aguilar et al., 2005; Chaplot et al., 2006; Tribe, 1992). Research has shown that depressions interrupt overland flow routing in a DEM and significantly alter defined flow directions used for hydrological parameter extraction (Lindsay and Creed, 2005; Grimaldi et al., 2007; Jenson, 1991). Numerous conditioning techniques have been developed to correct topographic depressions and enforce continuous downstream drainage (e.g. Jenson and Domingue, 1988; Planchon and Darboux, 2001; Wang and Liu, 2006; Rieger, 1998; Martz and Garbrecht, 1999). Each technique is characterized by its approach for handling DEM depressions. Depression filling and depression breaching techniques remain the most common drainage enforcement practices to date.

Although standard conditioning algorithms remove depressions and achieve downstream drainage, they cannot distinguish between actual and artifact features. This is particularly problematic in human-modified landscapes as a result of anthropogenic infrastructure. For example, human-designed road embankments often exhibit parallel drainage ditches and culvert underpasses that significantly influence regional overland flow routing and drainage network configuration. Water is typically diverted underneath road embankments; however, these diversion features are not captured within the two-dimensional DEM surface. As a consequence, artificial damming occurs along road embankment features (Duke et al., 2003). Although conditioning techniques remove depressions and ensure connected flow paths, they may also
remove or modify actual anthropogenic flow features that significantly influence local hydrological regimes.

Previous research has not adequately addressed the implications of various DEM conditioning methods on subsequent hydrological parameter extraction. Conditioning directly affects modelled stream networks and drainage divides. The development of various DEM conditioning methods has created uncertainty for accurate surface and near-surface flow path mapping. Understanding the effects of various DEM conditioning methods will be necessary for DEM optimization prior to hydrological applications.

1.2 Research Aim

This research assesses the impacts of various DEM properties on the spatial and statistical distribution of DEM-derived hydrological surface attributes. The following questions are asked:

[1] How does DEM grid resolution influence the definition of field-scale drainage divides and their downslope flowpath length patterns?

[2] How does DEM elevation source data impact field-scale drainage divides and downslope flowpath lengths?

[3] What are the effects of various DEM conditioning techniques on field-scale drainage divides and downslope flowpath lengths? What are some of the uncertainties associated with DEM conditioning?

1.3 Thesis Outline

Chapter 2 outlines and summarizes pertinent academic literature pertaining to surface water dynamics, DEMs, and hydrological modelling approaches that incorporate DEMs. Chapter 3 contains a detailed summation of the research methodology and results of this study. In addition, Chapter 3 discusses the implications of the research findings. To conclude, Chapter 4 summarizes the overall conclusions drawn from this research and offers considerations for future research efforts.
Chapter 2.0 Literature Review

2.1 Introduction

The following chapter synthesizes relevant literature pertaining to catchment hydrology, digital elevation models (DEMs), and hydrological modelling approaches that incorporate DEMs. Topography is emphasized as a main control of hydrological processes due to the inherent relationship between surface relief and downstream water discharge. DEM data acquisition, structure, and quality are reviewed. In addition, DEM surface derivatives are outlined to reflect the benefit of DEM integration in hydrological modelling applications. The associated methodologies for hydrological parameter extraction from DEMs are explored.

2.2 Catchment Hydrology

The term *catchment*, synonymous with *drainage basin* and *watershed*, can be defined as a natural unit of land in which water from a variety of inputs converges and flows downhill to a common outlet (Black, 1991). Catchments are the basic units of water supply and the controlling agents for water storage and flow regimes (Dunne and Black, 1970). Every catchment is a complex system with components that may significantly vary over time and space (Beven and Kirkby, 1979; Beven and Wood, 1983).

2.2.1 Variable Source Areas

The spatial and temporal variations associated with catchment characteristics and hydrological processes impede the development of clear and decisive perceptual models of hydrology (Beven and Wood, 1983; Beven and Kirkby, 1979). The variable source area concept, attributable to Hewlett and Hibbert (1967) and Dunne and Black (1970), recognizes the dynamic and three-dimensional nature of catchment runoff responses (Black, 1991; Beven and Wood,
The concept reflects the spatial and temporal variability of surface and subsurface runoff and also the varying response of a catchment to precipitation storm events (Beven and Wood, 1983; Dunne and Black, 1970; Hewlett and Hibbert, 1967; Quinn et al., 1991; Beven and Kirkby, 1979).

Due to the heterogeneous nature of catchment ground cover and topography, there is an inherent complexity in accurately predicting runoff-contributing areas (Beven and Wood, 1983). Variable source area hydrology specifically examines the role of topography and soil structure in the context of catchment overland flow dynamics (Beven, 2001). Water that reaches ground level has the capability to infiltrate the underlying geologic material and be stored in the subsurface portion of the catchment (Bakker and Anderson, 2011; Woods and Rowe, 1996; Black, 1991). The amount of water stored in the soil is dependent on the soil’s antecedent moisture conditions and permeability (Black, 1991). When soil becomes fully saturated, water is no longer infiltrated, resulting in overland flow (Horton, 1933). These saturated areas will expand and contract depending on the soil’s infiltration rate and drainage capacity, as well as storm frequency, all resulting in high temporal variability of runoff-producing areas across the catchment (Figure 2.1) (Walter et al., 2000; Beven and Wood, 1983; Beven, 2001; Woods and Rowe, 1996). High spatial variability in catchment soil composition also creates difficulties when predicting an entire catchment’s infiltration capacity or probability for surface runoff (Bakker and Anderson, 2011; Beven and Wood, 1983; Dunne and Black, 1970).

Numerous field studies have found that areas of high soil surface saturation often appear at the base of or convergence of hillslope features (e.g. Beven and Wood, 1983; Dunne and Black, 1970; Quinn et al., 1991). Topography is perhaps the best indicator of the gravitational potentials involved in both flow pathways and areas of high soil saturation, as water will always flow downslope to areas of low relief (Quinn et al., 1991; Dunne and Black, 1970). Catchment
geometry determines the convergence of both surface and subsurface flows because surface and subsurface water is directed to topographic hollows; subsurface flow is often proportional to a hydraulic gradient that is approximately equal to the ground-surface slope (Anderson and Kneale, 1982; Quinn et al., 1991; Hornberger et al., 1991; Beven and Kirkby, 1979). Due to this downslope movement of water, saturated areas of soil can be expected at the base of steep terrain (Beven and Wood, 1983; Quinn et al., 1991). The variable source area concept can be used to identify catchment regions that are most likely to produce surface runoff that directly contributes to surface water features (Walter et al., 2000). Variable source area hydrology provides a logical approach when modelling contributing areas by incorporating the inherent relationship between water flow and earth surface topography.

![Figure 2.1: Variable source area concept, displaying high temporal variability in runoff-producing areas across a catchment; as storm discharge (Q) increases over time (t), saturated, runoff-producing areas expand at areas of low relief or in close proximity to surface water features (adapted from Todd et al., 2006)](image-url)
2.3 Digital Elevation Models (DEMs)

Understanding catchment hydrology, and specifically surface flow pathways, involves significant knowledge of land surface characteristics. Topography can be used to develop more physically realistic models of hydrology due to the impact of surface relief on both surface and subsurface water flow (Moore et al., 1991; Quinn et al., 1991; Beven and Kirkby, 1979). Incorporating topographic attributes in hydrological modelling applications can significantly improve landscape representation and accurate flow path predictions. A digital elevation model (DEM) can be defined as a digital representation of the spatial distribution of earth surface elevations above a chosen datum (Moore et al., 1991; Fisher and Tate, 2006; Longley et al., 2005). DEMs are useful tools for assessing the spatial variability of hydrological processes because of their ability to digitally represent earth surface topography in a Geographic Information System (GIS) (Zhang and Montgomery, 1994; Moore et al., 1991).

2.3.1 DEM Data Acquisition

DEM creation requires the acquisition of earth surface elevation or height data. DEM data collection can be achieved through ground survey methods, topographic maps, and various remote-sensing techniques (Wise, 2007). Ground survey methods require manual point elevation data collection commonly achieved with surveying instruments such as Global Positioning Systems (GPS). The extensive labour costs and sampling times associated with manual techniques limit spatial survey extent. Ground surveying is therefore suited to smaller catchments (Heritage et al., 2009).

Elevation data may also be acquired from topographic map products. The earliest forms of DEMs were derived from topographic maps by digitizing contour lines of elevation data (Wise, 2007; Taud et al., 1999). This method is relatively simple and cost-effective because it
does not require manual field surveying (Taud et al., 1999; Longley et al., 2005). However, limitations may arise as a result of contour line spacing. The ground area between each contour line lacks recorded elevation data; interpolation is required between contour lines, resulting in generalized representations of the earth’s surface (Longley et al., 2005).

Remote sensing is the acquisition of data or information about a particular object of interest that does not involve physical contact with that object. Remote sensing methods can provide highly accurate elevation data through the use of either airborne or satellite sensors that measure the distance between the sensor and the earth surface below (Liu and Mason, 2009; Rabus et al., 2003). Photogrammetry is the process by which three-dimensional measurements of the earth surface are obtained using two or more aerial images based on stereoscopic parallax (Liu and Mason, 2009). The displacement of a point on the ground surface between two or more images is used to geometrically estimate that point’s distance from the imaging device, thus delivering an estimated elevation measurement (Liu and Mason, 2009; Longley et al., 2005). This method provides relatively accurate elevation results; however, it relies heavily on image clarity and point elevations that can be identified in more than one aerial image (Mayer, 1999).

Similarly, radar interferometry is another method that uses imagery. This method acquires two different images of the same ground region captured using radar sensors. The separation between the two sensors establishes a spatial baseline, permitting the measurement of topographic relief (Smith, 2002). Radar sensors deliver relatively accurate elevation data and are especially useful during nighttime acquisition events and poor atmospheric conditions (Madsen et al., 1993; Smith, 2002).

Laser altimetry is also a popular remote sensing method for acquiring ground surface elevation data. Laser altimetry, or light detection and ranging (LiDAR), collects extremely dense and highly accurate elevation data sets using lasers, GPS, and Inertial Navigation Systems (INS).
The LiDAR sensor transmits pulses of light which reflect off the terrain and other ground objects below. The return travel time of these light pulses is measured to derive distance values. The GPS records the position of every delivered pulse of light, while the INS records the laser orientation at the time of light emission (Liu and Mason, 2009; Baltsavias, 1999). The combination of each device’s information provides accurate and detailed surface elevations. LiDAR is an extremely beneficial data acquisition technique because of its high pulse frequency, multiple return features, and foliage penetration capabilities (Dassot et al., 2011; Baltsavias, 1999). LiDAR derived DEMs are particularly advantageous due to the high point densities of acquired elevation data and their associated low processing times (Liu and Mason, 2009).

2.3.2 DEM Data Structure

To create a DEM, point-based elevation data is interpolated into some form of data structure. There are three main DEM structures: the regular grid, the triangulated irregular grid (TIN), and the contour based formation (Shi et al., 2005; Gousie and Franklin, 2003; Lee, 1991). The regular grid, or raster DEM, is a digital grid surface whereby each square grid cell is assigned an elevation value based on the measurements from a supplying database. Every grid cell dimension represents the same amount of ground surface area, but reflects an averaged elevation value of that entire ground surface (Longley et al., 2005, Moore et al., 1991). TIN data structures use a set of non-overlapping, irregular-shaped triangles to represent earth surface elevations. Each triangle cell may vary in size according to topographic variation (Tachikawa et al., 1994; Moore et al., 1991). Lastly, the contour structure separates the digital landscape into irregular shaped quadrilaterals. These structures are based on overlapping networks of established contour lines and flowpath lines (Moore et al., 1991).
Regular grid DEMs are the most common data structure used by researchers. However, research has suggested that the regular grid is not an appropriate representation of the earth surface (Tachikawa et al., 1994; Shi et al., 2005). Regular grid DEMs maintain a uniform grid resolution that cannot necessarily account for large topographic variation in the landscape (Tachikawa et al., 1994; Maidment and Djokic, 2000; Moore et al., 1991). Grid resolution may be too coarse to properly represent surface variation or too fine, resulting in data redundancies (Raaflaub and Collins, 2006). The regular grid structure is therefore best suited for landscapes with limited topographic variation. Gridded DEMs still remain the most widely used data structures overall because of their low data storage requirements and computational efficiency in association with image-processing algorithms (Moore et al., 1991; Walker and Willgoose, 1999).

### 2.3.3 DEM Quality

DEM quality is important for all earth surface science applications. A DEM should be able to reflect highly accurate spatial distributions of land surface elevations for use in terrain analysis. Table 2.1 outlines the various factors that determine DEM quality.

**Table 2.1: Factors Affecting DEM Quality**

<table>
<thead>
<tr>
<th>Factors Affecting DEM Quality</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data acquisition methods and elevation source data characteristics</td>
<td>Walker and Willgoose, 1999; Garbrecht and Martz, 2000; Zhang et al., 2008; Zhang and Montgomery, 1994; Florinsky, 1998</td>
</tr>
<tr>
<td>DEM interpolation technique</td>
<td>Lindsay and Creed, 2005; Aguilar et al., 2005; Chaplot et al., 2006</td>
</tr>
<tr>
<td>DEM grid resolution</td>
<td>Kienzle, 2004; Wolock and Price, 1994; Zhang and Montgomery, 1994; Walker and Willgoose, 1999; McMaster, 2002; Clarke and Archer, 2009</td>
</tr>
</tbody>
</table>
Data acquisition techniques, and particularly derived elevation source data, can often limit DEM accuracy (Walker and Willgoose, 1999; Garbrecht and Martz, 2000; Zhang et al., 2008). Data precision is often linked to the density and distribution of ground elevation points. Research has shown that an increase in point sampling density can significantly increase DEM data precision and overall accuracy for hydrological applications (Zhang and Montgomery, 1994; Florinsky, 1998; Garbrecht and Martz, 2000).

DEM accuracy is also dependent on the employed interpolation algorithm. Despite the technical differences among all interpolation techniques, each algorithm can be used to estimate unknown elevation values from a group of known elevation values. A study by Aguilar et al. (2005) examined the effects of five interpolation techniques on DEM accuracy. Terrain morphology and sampling density of the source data were the greatest determinants of interpolation method quality. Similarly, a study by Chaplot et al. (2006) assessed the accuracy of five interpolation techniques. The researchers found that there were few differences between all methods when landscape morphology and elevation point densities were ignored. However, when source data point densities decreased, interpolation results varied. Although they dictate DEM accuracy to some degree, interpolation methods are highly dependent on the acquired elevation point data (Chaplot et al., 2006; Aguilar et al., 2005; Lindsay and Creed, 2005). A DEM interpolation algorithm should be chosen in consideration of the initial source data.

DEM$s are the basis of landscape representation in a variety of earth surface models. A DEM should be capable of displaying all topographic variations in a landscape. Accuracy can therefore be linked to the specific horizontal resolution of the DEM. The horizontal resolution can be defined as the user defined horizontal spacing of elevation points in the regular grid DEM (Anderson et al., 2006). Numerous studies have found that DEM surface derivatives, and particularly hydrological parameters, are extremely sensitive to horizontal grid resolution (e.g.
Kienzle, 2004; Wolock and Price, 1994; Zhang and Montgomery, 1994; Saulnier et al., 1997; Garbrecht and Martz, 2000; McMaster, 2002; Clarke and Archer, 2009). For example, Zhang and Montgomery (1994) and Wolock and Price (1994) both found that a decrease in horizontal grid resolution resulted in greater derived contributing areas for all DEM simulations. Coarse resolution DEMs can be problematic for earth surface modelling because they typically generalize topographic variation. Finer resolution DEMs are therefore well suited in highly variable landscapes. Resolution is the basis for scale in the DEM and should be set appropriately to model the landscape process of interest.

DEM-associated errors can be identified as either systematic or random (Wechsler, 2008; Fisher and Tate, 2006). These errors are often attributed to [1] data errors, relating to limited observations, poor spatial sampling, or outdated data; [2] measurement errors, such as position inaccuracy during data acquisition; and [3] processing errors, such as numerical inaccuracy or interpolation error (Li, 1994; Wechsler, 2008; Burrough and McDonnell, 1998; Fisher and Tate, 2006). The inherent errors associated with DEMs can propagate to DEM derived products and must therefore be accounted for throughout all modelling procedures (Fisher and Tate, 2006).
2.4 Using DEMs for Hydrological Modelling

2.4.1 Primary DEM Surface Derivatives

Progress in hydrological modelling applications has been the result of DEM integration techniques. DEMs are the primary source for land surface information that directly influences hydrological processes (Moore et al., 1991; Tarboton, 1997; O’Callaghan and Mark, 1984). Wilson and Gallant (2000) summarized primary surface derivatives, outlining attributes that can be directly calculated from a DEM surface (Table 2.2). A number of primary topographic derivatives are directly related to hydrological regimes and play a critical role in hydrological modelling applications (e.g. slope, upslope area, flowpath length) (Moore et al., 1991; Tarboton, 1997; Wilson and Gallant, 2000).
<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 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 slope</td>
<td>Mean slope of dispersal area</td>
<td>Rate of soil drainage</td>
</tr>
<tr>
<td>Catchment slope</td>
<td>Average slope over the catchment</td>
<td>Time of concentration</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>Dispersal area</td>
<td>Area downslope from a short length of contour</td>
<td>Soil drainage 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>

* Common attributes for hydrological applications
2.4.2 Flow Routing Algorithms

Understanding the hydrological connectivity of primary surface attributes is critical for subsequent hydrological analysis. The extraction of hydrological attributes from the DEM surface relies significantly on calculated overland flow routes to understand the distribution and transport of water across the landscape. Flow routing algorithms have been developed for use with gridded DEMs to determine the direction in which water from one grid cell may be distributed to any downslope, neighbouring grid cells (Tribe, 1992). There are two main types of flow algorithms: single flow direction algorithms (SFD) and multiple flow direction algorithms (MFD) (Wolock and McCabe, 1995). All flow routing techniques are capable of deriving a reasonable surface network of flow pathways; however, due to the unique approach developed for each individual algorithm, various methods can produce different outcomes of derived hydrological attributes. A number of flow routing algorithms have been incorporated in hydrological models, particularly the Deterministic 8 Neighbour (D8) (O’Callaghan and Mark, 1984) and D-infinity (Tarboton, 1997) algorithms.

Single flow direction algorithms essentially route water flow from the center of a DEM grid cell to one of the eight neighboring grid cells (Figure 2.2) (Arnold, 2010). O’Callaghan and Mark’s (1984) D8 algorithm is the most commonly used SFD technique used by researchers. The D8 technique is a basic flow algorithm that offers computational efficiency and flow direction from one grid cell to the neighboring cell with the lowest elevation value or steepest downhill descent (O’Callaghan and Mark, 1984). However, a number of studies have noted that the D8 method may produce unrealistic flow paths that are straight and parallel as a result of limiting flow to only one of eight possible grid cells (Erskine et al., 2006; Seibert and McGlynn, 2007; Wallis et al., 2009; Tribe, 1992). Determining overland flow direction is critical for any further hydrological DEM analysis. The D8 method is advantageous because it easily derives catchment...
boundaries and upslope contributing areas (Jenson and Domingue, 1988). The fundamental basis of the D8 algorithm has been a primary component in the development of other SFD and MFD algorithms.

Figure 2.2: Single flow direction (SFD) routing from midpoint (MP) of DEM grid cell to only one of neighboring eight grid cells

Similarly to SFD techniques, MFD algorithms also achieve overland flow route simulation. However, MFDs incorporate divergent flow by distributing flow from one cell into all neighboring grid cells with lower elevations (Freeman, 1991; Hengl and Reuter, 2008; Tribe, 1992). The D-infinity MFD algorithm developed by Tarboton (1997) remains the most commonly used MFD technique used to date (Erskine et al., 2006; Arnold, 2010). Figure 2.3 shows the conceptual design of the D-infinity technique. Connecting the eight grid cell centres creates eight triangle facets, each with a downslope vector. The flow direction associated with each grid cell is attributed to the direction of the steepest downslope vector from all eight facets (Tarboton, 1997). The D-infinity method eliminates the typical ‘over-dispersion’ effects
associated with MFD techniques, while overcoming the limitations associated with the D8 algorithm.

![Figure 2.3: Flow determination following Tarboton’s (1997) D-infinity multiple flow direction (MFD) technique; flow is directed along steepest downslope vector of eight triangular facets formed from midpoint (M) of centre grid cell](image)

**Figure 2.3** Topographic Depressions

DEMss contain characteristic spatial errors, commonly referred to as sinks, pits, or depressions (Grimaldi et al., 2007). Depressions can be described as DEM grid cells or groups of neighbouring grid cells that do not have a downslope drainage outlet; the surrounding cells possess higher elevation values, creating a topographic hollow (Jenson and Domingue, 1988). These spurious and artificial landscape features are often a result of data sampling and interpolation errors, as well as limited DEM resolution (Lindsay and Creed, 2006; Martz and Garbrect, 1998; Wolock and Price, 1994; Aguilar et al., 2005; Rieger, 1998). Figure 2.4 shows Martz and Garbrecht’s (1999) two-dimensional illustration of depressions caused by inaccurate elevation sampling. DEM depressions have been problematic in the past due to the belief that they create discontinuity in drainage pathways, negatively influencing natural hydrological
responses (Grimaldi et al., 2007). Standard DEM creation for hydrological modelling has therefore incorporated filling techniques to remove artifact depressions from the DEM surface (e.g. Jenson and Domingue, 1988; Planchon and Darboux, 2001).

![Figure 2.4: 2-D schematic of DEM grid surface; true elevations in white, underestimated and overestimated elevations in black; depressions (in gray) caused by overestimated and underestimated elevation values (adapted from Martz and Garbrecht, 1999)](image)

It should be noted that topographic depressions within DEMs are actually a combination of artifacts and true depression features (Lindsay and Creed, 2006; Grimaldi et al., 2007; Chou et al., 2004). True depressions are DEM depressions that represent actual topographic features in the landscape. Although less common, actual topographic depressions exist in glacial and karst landscapes, as well as human-modified landscapes (Duke et al., 2003). The increased topographic detail associated with fine resolution DEM data can reflect small-scale topographic variation leading to the identification of true depression features associated with human modifications to the landscape. For example, the construction of drainage ditches and detention ponds have been
shown to increase water drainage densities and modify surface drainage networks (Duke et al., 2003; Wemple et al., 1996). The existence of natural depression features provides cause for the development of modelling techniques that distinguish between actual and artifact depressions in DEM data (Lindsay and Creed, 2005; Lindsay and Creed, 2006).

2.4.4 Hydrological Modelling in Human-Modified Landscapes

Human-modified landscapes are notorious for altering the natural hydrological response of catchments. Anthropogenic landscape infrastructure, such as roads and embankments, significantly affect overland flow pathways and negatively influence downstream water discharge (Duke et al., 2003). In the absence of human-modifications, overland flow naturally gravitates from higher elevations to areas of low relief (Dunne and Black, 1970). However, road embankments and their associated parallel ditches alter a landscape’s natural flow pathways (Jones et al., 2000).

Anthropogenic structures are evident throughout all human-modified landscapes. However, these features are poorly represented in coarse resolution DEMs (Duke et al., 2003; Duke et al., 2006). DEM-based flowpath mapping applications have therefore been limited in human-altered landscapes. Duke et al. (2003; 2006) developed enforcement algorithms to incorporate road, ditch, and culvert data into DEMs. Their Road Enforcement Algorithm (REA) raises the elevations of roads and lowers the elevations of neighbouring ditches to construct more realistic drainage pathways. The development of fine-resolution LiDAR DEMs has revolutionized landscape representation, especially in human-modified landscapes. LiDAR DEMs can accurately portray anthropogenic linear features that impact overland flow due to their increased horizontal resolution (Schiess and Krogstad, 2003). However, the increased
topographic detail associated with LiDAR products can create challenges for hydrological DEM conditioning.

2.4.5 Hydrological DEM Conditioning

Hydrological conditioning techniques have been designed to ensure the removal or correction of problematic DEM depression features following DEM creation. ‘Hydrologically sound’ DEMs require a depression-less surface that maintains connectivity between all grid cells to enforce flow across the landscape. A number of conditioning techniques have been designed, each reflecting an inherent assumption regarding the true nature of depression features (e.g. Jenson and Domingue, 1988; Planchon and Darboux, 2001; Wang and Liu, 2006).

Smoothing, originally developed by Mark and Aronson (1984), is the original method for DEM drainage enforcement and depression correction. Smoothing replaces grid cell elevations with the average elevation value of the surrounding grid cells (Vieux, 1993). Researches have criticized this method as it often introduces additional information loss, alters DEM elevation values, and creates new depression features (Garbrecht and Martz, 1997; Jenson and Domingue, 1988). Additionally, smoothing decreases the spatial variability of elevations leading to generalized topography in a DEM (Vieux, 1993). However, Tarboton et al. (1991) found that derived drainage network density and arrangement are highly dependent on smoothing; when no smoothing was applied to DEMs, derived drainage networks were not discernable. Smoothing, prior to another conditioning method, is still recommended to reduce systematic errors and ensure drainage network derivation (O’Callaghan and Mark, 1984; Vieux, 1993; Garbrecht and Martz, 1997; Tarboton et al, 1991).

Filling and breaching are two common conditioning techniques for creating hydrologically sound DEMs. Filling techniques assume that all DEM depressions are artificial in
nature. These methods raise the elevation value of all depression cells to ensure downstream flow connectivity (e.g. Jenson, 1991; Jenson and Domingue, 1988; Planchon and Darboux, 2001). Breaching methods, however, lower the elevation of grid cells that neighbor depression cells to enforce downstream water transport. Breaching does not necessarily assume that all DEM depressions are artificial (Rieger, 1998).

Jenson and Domingue’s (1988) depression filling technique identifies all depression grid cells in a DEM and raises their elevation values to the elevation of the lowest neighboring grid cell. Similar to O’Callaghan and Mark’s (1984) original design, Jenson and Domingue’s (1988) method can resolve more complex DEM depressions. Planchon and Darboux (2001) introduced a new filling technique that simulates DEM ‘flooding’; the entire DEM surface is flooded and excess water is iteratively drained from each grid cell. The algorithm scans the DEM for upstream drainage networks or ‘trees’ by following flooded links. The highest elevation value in these flow paths is assigned to depression cells to raise their elevation and enforce downstream drainage.

Wang and Liu’s (2006) filling algorithm works similarly by incorporating a novel concept of spill elevation and a least-cost search technique for optimal flow paths. The algorithm defines a spill elevation for every DEM grid cell, defined as the minimum elevation value a cell needs to allow water to spill out to and reach an outlet cell on the edge of the DEM grid. The algorithm progressively determines spill elevation values for all DEM cells, beginning at an outlet cell and propagating to interior DEM cells. Since flow paths are searched from boundary outlets to interior cells, the condition maintains that elevation of connected cells on a flow path are non-decreasing. When depression cells are encountered in flowpath derivation, the depression cell must be raised to support the non-decreasing condition (Wang and Liu, 2006). Wang and Liu’s (2006) technique offers significant advancements over previously established methods.
Conventional methods require a process of marking depressions, delineating the catchments of those depressions, and identifying their pour points all before determining whether or not a cell actually needs to be filled or how high it should be filled to make a depressionless DEM (Wang and Liu, 2006). Wang and Liu (2006) also noted that memory requirements and processing time for their filling technique were minimal in comparison to the Jenson and Domingue (1988) and Planchon and Darboux (2001) methods, suggesting an overall increase in processing efficiency.

More recent filling techniques have adopted the assumption that DEM topographic depressions may actually reflect true landscape features. Such methods achieve flow enforcement by incorporating a ‘water layer’. For example, Arnold (2010) developed a filling technique that overlays a modelled water layer over the entire DEM grid surface to fill depressions. This ‘fill and overflow’ approach fills depressions with water until the water level reaches an outlet where overland flow would occur from the depression edge. Similarly, Rueda et al. (2013) developed a flooding algorithm for drainage network determination that does not require conventional conditioning of DEM depressions. A water layer fills depressions when required and also flows over flat areas to continue its course to surface water features.

While filling methods have become the most popular conditioning technique as a result of simplicity, breaching methods have evolved as an appropriate alternative to standard conditioning practices. Rieger (1992) designed a breaching technique using a phenomenon-based approach to prevent the elevation of depressions from being entirely lost. Former conditioning methods do not necessarily account for true depression features in the landscape. Instead of raising depression cells to a higher, spill elevation, the breaching method lowers grid cells along a breach channel, or trench, through a topographic barrier (Rieger, 1998). The breaching technique by Martz and Garbrect (1999) similarly lowers elevation pour points of a depression cell, creating a flow path to connect depression cells to a common DEM outlet cell. Breached channels are created between
depression cells and a distant grid cell with a lower elevation value. Difficulties arise as a result of multiple trench channel possibilities for each depression cell. Conventional breaching methods only consider straight trench channels, which may result in unnatural drainage network patterns (Martz and Garbrect, 1999; Lindsay and Creed, 2005).

The breaching technique by Dhun (2011) combines the standard breaching technique with a least-cost pathway approach. The method maintains the same breaching principle, however, a cost-distance is incorporated to determine the best possible trench pathway for each depression that results in the least modification to the DEM. This method is particularly advantageous in human-modified landscapes, where water discharge and drainage networks are highly influenced by anthropogenic infrastructure such as road embankments and imposed drainage ditches. For example, if there is a depression cell within a roadside ditch, the algorithm will trench a flow path along that ditch to a further location. Typical methods would automatically force a trench path through the road embankment; however, Dhun’s (2011) method calculates the cost of both outcomes. Enforcing drainage along ditches is less costly than lowering the elevation of road embankment grid cells. This novel technique is especially well suited for use with fine-resolution LiDAR DEMs that accurately model micro topographic variation and human-modifications to the landscape.

Drainage enforcement techniques have also been designed to incorporate ancillary landscape data. For example, ‘stream burning’, a technique first outlined by Hutchinson (1986), incorporates streamline data to produce sensible drainage networks in a DEM. A stream burning technique adapted for use in Whitebox GAT GIS software lowers or ‘burns’ elevation values (Z) in a DEM along a user-defined stream network such that:
\[ Z = E - (G/G + D)^k \times H \]

\( Z \) = newly calculated grid cell elevation (m)
\( E \) = old grid cell elevation (m)
\( G \) = grid resolution (m)
\( D \) = distance from a stream cell (m)
\( k \) = decay coefficient
\( H \) = elevation decrement (m)

Grid cells along the flowpath of an overlaid stream network – or ‘blue-line’ – are lowered by a user-defined interval: the elevation decrement value (H). Increasing decay coefficient (k) values result in steeper decrement gradients toward the overlaid streamline data (Lindsay, 2014). The stream burning method can create discrepancy between the original digital stream in the DEM and the trenched or ‘burned’ stream cells leading to dramatic topographic variations (Callow et al., 2007). The DEM’s digital stream will capture simulated flow from neighbouring hill slopes before it enters the burned stream cells. The decay coefficient is critical for maintaining natural riparian topography and minimizing the effect of parallel digital streams and burned streams (Callow et al., 2007; Hutchinson, 1986). While the stream burning method achieves surface drainage enforcement, it does not account for external depression features outside of the defined streamline data. Depression filling techniques are still required to maintain overland flow connectivity in areas that drain to surface water features.

Countless studies have been performed to analyze and determine the specific impacts of numerous DEM factors on derived terrain attributes. Researchers commonly assess the impacts of grid resolution, elevation data source, and interpolation methods on the quality of DEMs and their subsequent terrain derivatives; however, little is known about the effects of conditioning algorithms. Wenchsler (2000) investigated the impact of depression filling procedures on the representation of DEM elevations and slope. A significant bias was observed in slope derivations between filled and non-filled DEMs. Lindsay and Creed (2005) also evaluated the impacts of a
number of conditioning methods on DEMs, finding that depression removal significantly alters the spatial and statistical distribution of derived topographic attributes. Although these studies contribute an understanding of the effects of conditioning methods on topographic attributes, the specific investigation of hydrological parameter extraction remains unexplored. DEM conditioning directly influences topography and subsequent overland flow pathways.

2.5 Conclusion

Topography plays a critical role in the majority of earth surface processes. Overland flow is particularly dependent on surface geometry; water will accumulate at the base of steep terrain and at the convergence of hillslopes. Many researchers have therefore used topography as a direct indicator for surface water routing. Environmental modelling efforts have advanced to include computer-based analysis that optimizes our prediction of landscape activity. Using DEMs as a proxy for topographic information has significantly improved elevation estimates and terrain attribute detail.

Numerous studies have successfully utilized DEMs to understand and model hydrological earth surface regimes. The effects of various DEM variables on derived hydrological parameters have been widely investigated (e.g. grid resolution, elevation data source, interpolation method). However, the impacts of DEM conditioning techniques have not been adequately addressed. Understanding the effects of DEM conditioning techniques on derived hydrological parameters will be extremely important for accurate catchment delineation and drainage network configuration for hydrological modelling applications.
Chapter 3.0 Evaluating DEM conditioning techniques, elevation source data, and grid resolution for field-scale hydrological parameter extraction

3.1 Introduction

Topography is a main control of earth surface processes. Hillslope morphology directly influences surface and subsurface water flow due to the gravitational potential involved in flow pathways (Dunne and Black, 1970; Quinn et al., 1991; Beven and Wood, 1983). Understanding watershed hydrology involves significant knowledge of land surface characteristics. Topography can be used to develop more physically realistic models of hydrological processes due to the inherent relationship between surface relief and subsequent downstream water discharge.

Digital elevation models (DEMs) are commonly used to portray earth surface topography in a GIS. When combined with a GIS, DEMs are useful data for assessing the spatial variability associated with hydrological processes (Zhang and Montgomery, 1994). Raster DEMs, commonly referred to as regular-grid DEMs, are comprised of a collection of square tiles arranged in rows and columns. Each grid cell represents a corresponding area on the Earth’s surface as well as a coinciding point elevation value at the grid cell centre (Moore et al., 1991). Regular-grid DEMs are the most widely used data structures because of their low data storage requirements and computational efficiency in association with image processing algorithms (Moore et al., 1991; Walker and Willgoose, 1999).

DEMs have contributed substantially to progress in spatial hydrological modelling over the past several decades. DEMs are useful for a number of common hydrological applications, such as watershed delineation (Jenson and Domingue, 1988; Jenson, 1991), stream network extraction (O’Callaghan and Mark, 1984; Tarboton, 1997), and surface and near-surface flowpath mapping (Erskine et al., 2006; Costa-Cabral and Burges, 1994). Advanced techniques in
elevation data acquisition, DEM interpolation, and hydrological DEM conditioning have revolutionized DEM accuracy and the extraction of topographic derivatives from the digital terrain surface.

Advancements in automated DEM analysis techniques have allowed researchers to transfer derived DEM surface parameters into meaningful inputs for hydrological models (Jenson and Domingue, 1988; Martz and Garbrecht, 1998). A number of automated methods for topographic parameter extraction from DEMs exist in GIS environments. Environmental process models perform a watershed parameterization process involving watershed boundary and channel network delineation, as well as contributing area identification (Armstrong and Martz, 2003). Automated DEM delineation methods ultimately rely on two critical factors: [1] a method for overland flow routing to define contributing areas and channel networks, and [2] a method for managing topographic depression features and flat areas that inhibit overland flow (Martz and Garbrecht, 1998).

Flow paths in DEMs are created based on elevation differences among flow-originating grid cells and their downslope neighbouring grid cells. Flow routing algorithms can be described as any method that determines the direction in which water travelling over the topographic surface from one cell may be distributed to any downslope, neighbouring cells (Tribe, 1992). Each flow routing method has a unique approach for deriving hydrological attributes such as catchment area and upslope contributing area. Algorithms such as the D8 (O’Callaghan and Mark, 1984) and D-infinity (Tarboton, 1997) have been incorporated into hydrological models as methods for overland flow routing prior to watershed parameterization.

Topographic depressions, often termed as sinks or pits, are characteristically prevalent in DEMs. Depressions can be defined as individual cells or group of neighbouring cells that do not have a downslope flow outlet cell (Jenson and Domingue, 1988). Surrounding grid cells possess
higher elevation values resulting in a topographic hollow. DEM depressions are particularly problematic for overland flow simulation because they accumulate water, creating discontinuity in flow pathways and negatively influencing the modelled hydrological response of a catchment (Lindsay and Creed, 2005; Grimaldi et al., 2007).

DEM conditioning techniques have been developed to resolve the negative effects associated with topographic depression features. Each conditioning technique is based on an assumption regarding the true nature of depressions. Topographic depressions are actually a combination of artifact and actual depression features (Lindsay and Creed, 2006; Grimaldi et al., 2007). Artifact depressions typically result from elevation data inaccuracy, interpolation error, and limited data resolution (Walker and Willgoose, 1999). Actual depressions, however, represent true topographic features in the landscape (Lindsay and Creed, 2005). Though less common than artifact depressions, real depressions exist in most non-fluvial landscapes, including glacial and karst landscapes.

Hydrological DEM conditioning techniques are distinguished by their approach for accommodating depression features. Every technique is designed to enforce flow across a landscape by connecting flow path grid cells, creating a hydrologically sound DEM. Depression filling (e.g. Jenson and Domingue, 1988; Planchon and Darboux, 2001; Wang and Liu, 2006), depression breaching (e.g. Rieger, 1998; Dhun, 2011), and stream burning (e.g. Hutchinson, 1989) are the most common types of drainage enforcement methods. Filling techniques remove depression features by raising the elevation value of a depression cell. Breaching, however, works to lower the grid cells that are adjacent to depression cells (Rieger, 1998). Stream burning uses digital streamline data to reinforce mapped drainage networks in a DEM. Elevation values in a DEM along a mapped stream network are lowered, or ‘burned’ into the elevation model (Hutchinson, 1989).
Traditional flow enforcement methods resolve DEM depressions quite well; however, their effectiveness in human-modified landscapes has been limited. Dhun (2011) developed a novel breaching technique to accommodate the linear flow paths associated with anthropogenic landscapes, such as agricultural drainage ditches. The construction of various landscape infrastructures has been shown to increase downstream water discharge and modify surface drainage networks (Duke et al., 2003). Conditioning is highly dependent on the landscape reflected by the elevation model.

Recent developments in hydrological and erosion-based modelling rely heavily on the integrity of available DEMs. The effects of various DEM grid resolutions and source data on subsequent modelling practices have been investigated (e.g. Zhang and Montgomery, 1994; Walker and Willgoose, 1999). Optimal hydrological DEM conditioning techniques, however, remain unaddressed by conventional modelling practices that strictly remove DEM topographic depressions to enforce flow connectivity. Advancements in DEM conditioning methods present new challenges for DEM optimization prior to use in advanced environmental models. Conditioning dictates DEM landscape representation; hydrological surface derivatives can be significantly impacted by different conditioning techniques. The purpose of this study is to examine and evaluate the effects of various DEM grid resolutions, elevation source data, and hydrological conditioning techniques on field-scale hydrological parameter extraction and distribution. This study aims to assess the uncertainty associated with each DEM property. In this case, uncertainty refers to data precision, or the degree to which derived hydrological parameters vary when grid resolution, source data, and conditioning technique changes.
3.2 Data and Methodology

3.2.1 Study Area

The study was conducted using elevation data acquired from the Rondeau Basin (42°17’N 81°52’W), a Lake Erie coastal zone in Kent County, southwestern Ontario, Canada (Figure 3.1). The northeastern portion of the basin runs east to west along the Blenheim moraine, resulting in gently undulating topography towards the centre of the basin and gently sloping topography leading away from the moraine. Deep gullies drain the northern portion of the watershed, with flow reaching the thirteen main tributaries that drain south to Lake Erie (Gilbert and Locke, 2007). These features constitute a portion of the approximately 12,000 ha Rondeau watershed. The dominant land use in the region is agriculture. Gentle topography, mild climate, and rich, silt-loam soils provide ideal conditions for productive agricultural activity (Day et al., 1977). Intensive farming practices produce increased agricultural runoff, exacerbating high nutrient and sediment loading from local fields to adjacent draining tributaries.

Figure 3.1: Hillshade image of Rondeau Watershed study area in Southwestern Ontario
3.2.2 Data

**Provincial DEM**

A publicly accessible DEM was collected for the study area: the 2006 Ontario Provincial Tiled DEM Dataset, produced by the Ontario Ministry of Natural Resources (OMNR) at a 10 m grid resolution. Produced for hydrological feature mapping applications, the provincial DEM is also used for a broad range of research in the fields of forestry, ecology, and climatology. Interpolation techniques are outlined in section 3.2.3.

**LiDAR DEMs**

LiDAR data over the study area were acquired over a two-day period (May 4<sup>th</sup>/5<sup>th</sup>) in the spring of 2008. Raw point cloud LiDAR data were obtained from the Ontario Ministry of Agriculture and Food (OMAF) in LAS file format. The point cloud was used to interpolate three LiDAR DEMs at 10 m, 5 m and 1 m resolutions. The interpolation and processing techniques used for this dataset are described in the following sections.

**Ontario Hydro Network (OHN)**

The Ontario Hydro Network (OHN), a 1:10,000 stream network dataset, was used as reference data to compare delineated stream networks in each DEM to surveyed surface stream networks in the Rondeau catchment. The OHN was projected in UTM Zone 17 Datum NAD 83. This stream data was also used as ancillary data for the stream burning drainage enforcement technique outlined in section 3.2.4.

**Agricultural Resource Inventory (ARI) Field Polygon Layer**

The objective of the Agricultural Resource Inventory (ARI) dataset is to indicate geographic land use information. This includes individual agricultural field boundaries and non-agricultural land cover (e.g. urban, forest, homestead). The 2013-updated ARI field polygon dataset for Kent County was obtained from OMAF. The ARI layer was projected in UTM Zone
17 Datum NAD 83 at a scale of 1:10,000. ARI field polygons were used to create and derive individual raster field boundaries to be used as flow outlet cells in field upslope contributing area identifications, as outlined in section 3.2.5.

### 3.2.3 DEM Interpolation

#### 10 m Provincial DEM

The provincial DEM was previously interpolated by the OMNR using five main datasets: [1] Contour Line Data; [2] Ontario Base Map-Digital Terrain Model (OBM-DTM); [3] Spot Heights; [4] Water Features Areas; and [5] Water Virtual Flows. Elevations were interpolated from contour line data, including the OBM Contour dataset. Spot heights were used in areas where OBM data was unavailable. The spot height data was also used in conjunction with the water feature area polygon dataset to identify all surface water features and record their spot elevations. Lastly, the water virtual flow data was used to enforce flow and ensure downstream drainage associated with the identified channels in the water feature polygon layer.

#### 10 m, 5 m, and 1 m LiDAR DEMs

Whitebox Geospatial Analysis Tools (GAT) 3.1.0 (Lindsay, 2014) GIS software was used to interpolate the Rondeau LiDAR point cloud data. The computationally efficient inverse distance weighting (IDW) method was used to interpolate a 10 m, 5 m, and 1 m gridded LiDAR DEM from the Rondeau dataset (Lu and Wong, 2008). Due to the dense and highly accurate LiDAR dataset, greater weight was assigned to nearby points using a high distance-decay parameter. This method is equally as effective as the nearest neighbor interpolation technique; however, assigning a weighting to nearby points using the IDW technique resulted in minor smoothing that corrected the roughness associated with flight-line overlap areas. The particular IDW interpolation algorithm in Whitebox GAT incorporates a maximum scan angle deviation.
parameter that helps to reduce the roughness effects associated with large variation in scan angles near the edges of scan lines. These variations in scan angles can significantly impact modelled surface flowpaths in areas where flight lines overlap. A low maximum scan angle deviation parameter was used to reduce the roughness associated with overlapping scan lines.

Data points classified as vegetation or building features were excluded from interpolation; only last return points were incorporated in the IDW procedure. Using last returns and excluding external surface features produces a DEM that reflects ground surface elevations that are significant for overland flow simulation. Remaining off-terrain objects were removed and a mean $3 \times 3$ filter was applied to reduce noise in the image.

### 3.2.4 DEM Conditioning

The impacts of three common conditioning techniques were examined on each interpolated DEM. These techniques included:

1. Depression filling (Wang and Liu, 2006);
2. Depression breaching (Dhun, 2011);

Each technique was used to create different hydrologically corrected DEMs for each DEM dataset in Whitebox GAT for a total of 12 DEMs (4 DEMs $\times$ 3 conditioning methods) (Table 3.1).
Table 3.1: 12 DEMs derived from 2006 10 m Provincial tiled DEM, IDW interpolated 10 m, 5 m, and 1 m LiDAR DEMs (table demonstrates variation in DEM grid resolution, elevation data source, and hydrological conditioning technique)

<table>
<thead>
<tr>
<th>GRID RESOLUTION</th>
<th>ELEVATION DATA SOURCE</th>
<th>CONDITIONING TECHNIQUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 m Provincial DEM</td>
<td>10 m LiDAR DEM</td>
<td>5 m LiDAR DEM</td>
</tr>
</tbody>
</table>

Various algorithms have been developed for depression detection and filling (e.g. Jenson and Domingue, 1988; Planchon and Darboux, 2001). Wang and Liu’s (2006) algorithm offers significant advancements over previous methods, including minimal memory requirements and processing time. Depression breaching is another drainage enforcement technique that provides an alternative to standard depression filling methods. The breaching technique outlined by Dhun (2011) was used in Whitebox GAT to generate a hydrologically sound DEM for each outlined DEM dataset. Dhun’s (2011) breaching algorithm is especially useful in human-modified landscapes that exhibit anthropogenic linear flow path features, similar to agricultural drainage ditches imposed throughout the Rondeau watershed.

A stream burning method adapted for use in Whitebox GAT was used to generate the remaining hydrologically corrected DEMs. The OHN vector dataset for Kent County was used as
the reference streamline data for the stream burning technique. The OHN vector dataset is highly accurate for identifying channel features in the landscape; the blue-line commonly overlaps the DEM’s digital stream network, minimizing and often eliminating potential for parallel stream distortion. Following the stream burning operation, the Wang and Liu (2006) filling algorithm was applied to each burned DEM to ensure landscape connectivity for subsequent hydrological parameter extraction.

3.2.5 Spatial Distribution of Upslope Contributing Areas (UCA)

The spatial distribution of upslope contributing area (UCA) was used to evaluate the impact of grid resolution, data source, and conditioning method on hydrological parameter extraction. UCA is fundamental in hydrological models, as it represents the area that can potentially produce overland flow to a location of interest (Tarboton et al., 1991; Quinn et al., 1991). The D8 flow direction algorithm (O’Callaghan and Mark, 1984) was used to assign flow directions to all DEM grid cells. Individual ARI raster field boundaries were used as the various target cells or ‘outlets’ for field-scale flow accumulation. A simple boundary tool was used to identify field-scale contributing areas for all field edges, producing multiple sub-basins for each field. The spatial impact of resolution, data, and conditioning was defined as the percent area in disagreement among field-scale contributing areas derived from DEMs with differing hydrological pre-processing techniques, source data, and resolutions.

3.2.6 Statistical Distribution of Downslope Flowpath Lengths (DFL)

Downslope flowpath lengths (DFL) were derived for field contributing areas in each DEM to assess the impact of resolution, data, and conditioning on DEM statistical distributions. DFL is an important variable in hydrological analysis because it reflects distance to a catchment outlet along an overland flowpath; this is particularly significant for understanding the timing of
flow to a specific outlet (Liu et al., 2003). DFL was derived for the field-scale UCAs delineated in section 3.2.5 for all DEMs.

Kolmogorov-Smirnov (K-S) two-sample tests were used to evaluate whether resolution, data, or conditioning technique significantly affected the statistical distribution of DFL distributions between various DEMs. Through random sampling, the K-S test determines whether the maximum difference ($D_{\text{max}}$) between the cumulative probability distributions of two samples is greater than expected (Norcliffe, 1982). The K-S test is a non-parametric statistical test, suitable when data does not fit a normal distribution. K-S tests are also sensitive to differences in both sample distribution location and shape, which is particularly important for assessing the effects of conditioning techniques. Depression removal affects distribution tails because pits commonly occur in areas of lower elevation (Rieger, 1998).

A total of 36 K-S tests were conducted to assess grid resolution, data source, and DEM conditioning methods. Tests were performed on random samples of grid cells throughout each DEM. Sample size in each case reflected approximately 0.02% of the total number of grid cells in each DEM (10 m DEMs, n = 1,500; 5 m DEM, n = 7,800; 1 m DEM, n = 189,000).

3.3 Results

3.3.1 Spatial Analysis

Grid Resolution

The percentage of total field contributing areas in disagreement among the 10 m, 5 m, and 1 m DEMs are displayed in Figure 3.2. The depression filling (DF) scenarios for all three DEM resolution comparisons produced the highest percentage of UCA in disagreement. For example, the filled 10 m and 1 m DEM comparison yielded 37.3% disagreement, while the remaining 10 m
and 1 m comparisons showed 29.9% and 29.4% for breaching (DB) and burning (SB), respectively. Disagreement was higher for all 10 m and 1 m comparisons.

**Figure 3.2:** Spatial differences in field derived UCA between 10 m and 5 m LiDAR DEMs, 5 m and 1 m LiDAR DEMs, and 10 m and 1 m LiDAR DEMs (varying resolution) as indicated by % area in disagreement (DF = Depression Filling; DB = Depression Breaching; SB = Stream Burning)

*Elevation Data Source*

Total field contributing area in disagreement between the 10 m provincial DEM and the 10 m LiDAR DEM is shown in Figure 3.3. Area of disagreement between each DEM ranges closely from 39.9% for the burned DEM comparison to 47.5% for the filled comparison. The breached DEMs fall close to filled at 46.9%.
Figure 3.3: Spatial differences in field derived UCA between 10 m Provincial DEM and 10 m LiDAR DEM (varying elevation data source) as indicated by % area in disagreement (DF = Depression Filling; DB = Depression Breaching; SB = Stream Burning)

**Conditioning Technique**

The percentage of total field contributing areas in disagreement among various conditioned DEMs is displayed in Figure 3.4. A similar range of percent UCA disagreement is evident for each comparison. The filling and breaching comparisons range from 12.9% to 36.5%; filling and burning from 14.3% to 31.2%; and burning and breaching from 15.2% to 37%. Highest disagreement in UCA for each individual DEM is evident in burned and breached comparisons. The lowest percentages of UCA disagreement occur in the 10 m provincial DEM comparisons. In every scenario, the area of disagreement almost doubles when the 1 m LiDAR is used for comparison, with the 10 m LiDAR and 5 m LiDAR often falling midway between the minimum and maximum UCA in disagreement.
3.3.2 Statistical Analysis

Grid Resolution

K-S tests were used to evaluate the effect of DEM grid resolution on DFL distributions. Tables 3.2-3.4 note the $D_{\text{max}}$ values between the DFL distributions derived from each DEM as well as the significance of the differences. The $D_{\text{max}}$ values of the tested filled, burned, and breached 1 m, 5 m, and 10 m DEMs ranged from 0.137-0.291. Significance values of <0.001 were common throughout.

Figure 3.4: Spatial differences in field derived UCA between various DEM conditioning techniques as indicated by % area in disagreement (DF = Depression Filling; DB = Depression Breaching; SB = Stream Burning)
Table 3.2: Tests for statistically significant differences in field derived DFL distributions between 1 m and 10 m LiDAR DEMs as indicated by K-S test p-value (note: significance at 95% confidence level)

<table>
<thead>
<tr>
<th>10 m LiDAR DEM</th>
<th>Depression Filling</th>
<th>Depression Breaching</th>
<th>Stream Burning</th>
</tr>
</thead>
</table>
| 1 m LiDAR DEM  | \( D_{\text{max}} = 0.188 \)  
\( p\)-value < 0.001 |                      |                      |
| Depression Breaching | \( D_{\text{max}} = 0.260 \)  
\( p\)-value < 0.001 |                      |                      |
| Stream Burning  |                      |                      | \( D_{\text{max}} = 0.157 \)  
\( p\)-value < 0.001 |

Table 3.3: Tests for statistically significant differences in field derived DFL distributions between 5 m and 10 m LiDAR DEMs as indicated by K-S test p-value (note: significance at 95% confidence level)

<table>
<thead>
<tr>
<th>10 m LiDAR DEM</th>
<th>Depression Filling</th>
<th>Depression Breaching</th>
<th>Stream Burning</th>
</tr>
</thead>
</table>
| 5 m LiDAR DEM  | \( D_{\text{max}} = 0.137 \)  
\( p\)-value < 0.001 |                      |                      |
| Depression Breaching | \( D_{\text{max}} = 0.165 \)  
\( p\)-value < 0.001 |                      |                      |
| Stream Burning  |                      |                      | \( D_{\text{max}} = 0.291 \)  
\( p\)-value < 0.001 |

Table 3.4: Tests for statistically significant differences in field derived DFL distributions between 1 m and 5 m LiDAR DEMs as indicated by K-S test p-value (note: significance at 95% confidence level)

<table>
<thead>
<tr>
<th>5 m LiDAR DEM</th>
<th>Depression Filling</th>
<th>Depression Breaching</th>
<th>Stream Burning</th>
</tr>
</thead>
</table>
| 1 m LiDAR DEM  | \( D_{\text{max}} = 0.160 \)  
\( p\)-value < 0.001 |                      |                      |
| Depression Breaching | \( D_{\text{max}} = 0.276 \)  
\( p\)-value < 0.001 |                      |                      |
| Stream Burning  |                      |                      | \( D_{\text{max}} = 0.208 \)  
\( p\)-value < 0.001 |
The DFLs derived from the 10 m provincial and 10 m LiDAR DEMs were tested to highlight significant differences as a result of varying source data. Table 3.5 presents the D\textsubscript{max} values and significance of differences. D\textsubscript{max} values for the burned, filled, and breached DEM pairs ranged from 0.065-0.108 respectively. Testing showed significant differences in DFL distributions among the filled and breached DEM pairs.

### Table 3.5: Tests for statistically significant differences in field derived DFL distributions between 10 m LiDAR DEM and 10 m Provincial DEM (varying elevation source data) as indicated by K-S test p-value (note: significance at 95% confidence level)

<table>
<thead>
<tr>
<th>10 m Provincial DEM</th>
<th>Depression Filling</th>
<th>Depressed Breaching</th>
<th>Stream Burning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depression Filling</td>
<td>D\textsubscript{max} = 0.092</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>p-value 0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression Breaching</td>
<td></td>
<td>D\textsubscript{max} = 0.108</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>p-value 0.002</td>
<td></td>
</tr>
<tr>
<td>Stream Burning</td>
<td></td>
<td></td>
<td>D\textsubscript{max} = 0.065</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>p-value 0.174</td>
</tr>
</tbody>
</table>

### Conditioning Technique

K-S tests were used to examine the effect of DEM conditioning methods on DFL distributions. Tables 3.6-3.9 show the results of K-S tests for each conditioning technique used on the four separate DEMs. The 10 m provincial DEM (Table 3.4) had a range of D\textsubscript{max} values between 0.014 and 0.091. Higher D\textsubscript{max} values corresponded with statistically significant differences in DFL distributions among conditioning techniques. When tested against each other, stream burning and depression filling methods showed statistical significance with low p-values. Similarly, the depression breaching and stream burning comparison test showed statistical significance in DFL. The test for breaching and filling produced no statistical difference in DFL.
distributions. The 10 m LiDAR DEM (Table 3.7) tests produced very similar \( D_{\text{max}} \) values for each conditioning method comparison; values ranged from 0.041-0.048. K-S tests indicated no statistical difference in DFL distributions among any conditioning method comparison. \( D_{\text{max}} \) values for the 5 m LiDAR DEM tests (Table 3.8) ranged from 0.017-0.042 with K-S tests showing statistical differences for breaching and burning and breaching and filling comparisons. The 1 m LiDAR DEM test results (Table 3.9) produced a range of \( D_{\text{max}} \) values from 0.056 to 0.152. K-S tests also produced high significance values for all conditioning comparison tests (\( p \)-value <0.001).

Table 3.6: Tests for statistically significant differences in DFL distributions between 3 conditioned 10 m Provincial DEMs as identified by K-S test \( p \)-value (note: significance at 95% confidence level)

<table>
<thead>
<tr>
<th>10 m Provincial DEM</th>
<th>Depression Filling</th>
<th>Depression Breaching</th>
<th>Stream Burning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depression Filling</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression Breaching</td>
<td>( D_{\text{max}} = 0.014 )</td>
<td>( p )-value 1.000</td>
<td></td>
</tr>
<tr>
<td>Stream Burning</td>
<td>( D_{\text{max}} = 0.091 )</td>
<td>( p )-value 0.022</td>
<td>( D_{\text{max}} = 0.079 )</td>
</tr>
</tbody>
</table>

Table 3.7: Tests for statistically significant differences in DFL distributions between 3 conditioned 10 m LiDAR DEMs as indicated by K-S test \( p \)-value (note: significance at 95% confidence level)

<table>
<thead>
<tr>
<th>10 m LiDAR DEM</th>
<th>Depression Filling</th>
<th>Depression Breaching</th>
<th>Stream Burning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depression Filling</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression Breaching</td>
<td>( D_{\text{max}} = 0.042 )</td>
<td>( p )-value 0.682</td>
<td></td>
</tr>
<tr>
<td>Stream Burning</td>
<td>( D_{\text{max}} = 0.048 )</td>
<td>( p )-value 0.509</td>
<td>( D_{\text{max}} = 0.041 )</td>
</tr>
</tbody>
</table>
Table 3.8: Tests for statistically significant differences in DFL distributions between 3 conditioned 5 m LiDAR DEMs as indicated by K-S test p-value (note: significance at 95% confidence level)

<table>
<thead>
<tr>
<th>Depression Filling</th>
<th>Depression Breaching</th>
<th>Stream Burning</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 m LiDAR DEM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression Filling</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression Breaching</td>
<td>$D_{\text{max}} = 0.042$</td>
<td>$p$-value 0.004</td>
</tr>
<tr>
<td>Stream Burning</td>
<td>$D_{\text{max}} = 0.017$</td>
<td>$D_{\text{max}} = 0.039$</td>
</tr>
<tr>
<td>$p$-value</td>
<td>0.638</td>
<td>0.007</td>
</tr>
</tbody>
</table>

Table 3.9: Tests for statistically significant differences in DFL distributions between 3 conditioned 1 m LiDAR DEMs as indicated by K-S test p-value (note: significance at 95% confidence level)

<table>
<thead>
<tr>
<th>Depression Filling</th>
<th>Depression Breaching</th>
<th>Stream Burning</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 m LiDAR DEM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression Filling</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depression Breaching</td>
<td>$D_{\text{max}} = 0.122$</td>
<td>$p$-value &lt;0.001</td>
</tr>
<tr>
<td>Stream Burning</td>
<td>$D_{\text{max}} = 0.152$</td>
<td>$D_{\text{max}} = 0.056$</td>
</tr>
<tr>
<td>$p$-value</td>
<td>&lt;0.001</td>
<td>0.132</td>
</tr>
</tbody>
</table>

3.4 Discussion

3.4.1 Spatial and Statistical Differences Associated with Various DEM Grid Resolutions

The effects of DEM grid resolution on subsequent hydrological parameter extraction have been widely investigated. Kienzle (2004) found that upslope contributing area identification depends strongly on DEM resolution. The results of the present study confirm the results of Kienzle (2004) indicating that approximately 30-37% of total derived field-scale UCAs were in disagreement for all 10 m and 1 m LiDAR DEM comparisons, regardless of conditioning technique. The 10 m and 5 m DEM comparisons ranged from 11-17%, while the 5 m and 1 m comparisons were between 22% and 30%. Simulations that included the 1 m LiDAR DEM as a
comparison produced greater differences in derived UCA, demonstrating the effect of finer resolution data on spatial hydrological modelling. Figure 3.5 shows a field in the Rondeau watershed following UCA delineation in the 10 m LiDAR DEM and 1 m LiDAR DEM. The two images demonstrate a variation in drainage divides for each derived field-basin. The 1 m DEM delineates four contributing areas to individual field boundaries, whereas the 10 m DEM delineates two larger, more generalized, contributing areas for the same field. The two remaining sub-basins draining to the left and bottom field edges are severely truncated in the 10 m DEM. Studies confirm that decreased DEM resolution results in more generalized contributing areas, especially in small catchments (Wolock and Price, 1994; Zhang and Montgomery, 1994; Saulnier et al., 1997). For field-scale analysis, this is obviously even more problematic.

Figure 3.5: UCA delineation on Rondeau field in 10 m LiDAR DEM (a) and 1 m LiDAR DEM (b); note differences in drainage divides and subsequent derived field sub-basins as a result of DEM resolution
K-S tests for statistical differences in derived DFL distributions between each DEM produced p-values <0.001 for all simulations (Table 3.2-3.4). Significant differences in DEM distributions were evident for all comparisons, indicating that grid resolution is a major factor in the distribution of hydrological parameters. Grid cell size has been shown to significantly affect the cumulative frequency distributions of contributing area, topographic index, and hydrological simulations (Zhang and Montgomery, 1994).

Stream patterns derived from coarse resolution DEMs must rely on large-scale topographic features to develop flow patterns. Finer-resolution DEMs have significantly improved landscape detail to overcome the potential misrepresentation associated with coarse DEM grids. Walker and Willgoose (1999) and Zhang and Montgomery (1994) suggest that a 10 m DEM grid resolution presents the best compromise for simulating hydrological processes at the watershed scale. However, at the hillslope and field scale, fine-resolution LiDAR DEMs are better suited for modelling hydrological processes. The 1 m LiDAR DEM can identify small-scale surface accumulation features that cannot be modelled by the 10 m DEM due to coarser grid resolution. Many agricultural watersheds have been altered by human-modifications such as drainage ditch construction. The 1 m LiDAR DEM accommodates these features in contributing area identification. Differences in derived UCA and DFL distributions between coarse and fine resolution DEMs are a result of variations in DEM topographic detail.

3.4.2 Spatial and Statistical Differences Associated with Various DEM Elevation Source Data

DEM accuracy is typically linked to elevation source data. DEM surface derivatives can therefore be sensitive to initial elevation data used in DEM creation. Spatial analysis results demonstrate a range of approximately 40%-47.5% disagreement in derived field UCA between 10 m LiDAR and 10 m provincial DEM comparisons. Again, a similar range showed consistency
among all tests, indicating no resulting implications from imposed conditioning methods (Figure 3.3). The range of disagreement for DEM source data comparison was larger than the range examined for grid-resolution comparisons (Figure 3.2), suggesting that source data, in this case, greatly influenced variations in hydrological attribute derivation.

Statistical differences in DFL distributions among the 10 m provincial and 10 m LiDAR DEM comparisons were significant for only the depression filling and depression breaching K-S tests (Table 3.5). The spatial differences that resulted from varying source data were also expected during statistical analysis; however, the stream burning comparison between the 10 m LiDAR and 10 m provincial DEMs was found to be insignificant with a random sample size of 1500 grid cells. The 10 m provincial DEM was interpolated using the OHN streamline data. Using the OHN as ancillary data for the stream burning analysis of the 10 m LiDAR DEM may have prevented statistically significant differences in the distribution of DFLs between the provincial and LiDAR data sets as a result of common drainage network configurations. Although, the $D_{\text{max}}$ values determined from the three K-S tests range from approximately 0.07-0.1, indicating a low variation in actual DFL distributions for each DEM simulation.

Research indicates that DEMs are commonly limited by their original elevation source data (e.g. Walker and Willgoose, 1999; Garbrecht and Martz, 2000; Florinsky, 1998; Zhang et al., 2008). Walker and Willgoose (1999) found that the underlying data source used for deriving DEMs is a major determinant of surface derivatives and a crucial factor in observed differences between those derivatives. Elevation data can significantly vary in terms of data type and data collection. The 10 m provincial DEM was derived from past contour elevation data and specific spot height elevation data. Contour data and spot elevations, however, can be grossly inaccurate (Robinson, 1994; Zhang and Montgomery, 1994). Variation in DEM source data between the LiDAR and provincial DEMs perhaps resulted in subsequent variations in corresponding grid cell
elevations. Different elevation assignments may have resulted in different UCAs and DFL distributions.

3.4.3 Spatial and Statistical Differences Associated with Various DEM Conditioning Techniques

Topographic depressions are ubiquitous in all DEMs as a result of data collection and data interpolation error as well as limited DEM resolution. Conditioning methods that overcome the negative hydrological impacts associated with depressions achieve drainage enforcement in a number of ways. The three conditioning methods assessed in this study showed some significant spatial and statistical differences in derived UCA and DFL. The spatial analysis revealed relatively similar ranges in percent UCA in disagreement between each comparison. Depression filling and depression breaching comparisons for all four DEM scenarios showed a range of approximately 13%-37% (Figure 3.4). Depression filling versus stream burning and depression breaching versus stream burning showed similar ranges from 14%-31% and 15%-37%, respectively. Variation in UCA disagreement between different conditioning methods was low for all DEMs. The 10 m provincial DEM had a disagreement range from 13%-15% in all three conditioning comparisons. The 10 m LiDAR and 5 m LiDAR DEMs had relatively similar ranges between 18%-23% and 19%-24% respectively. The 1 m LiDAR DEM comparisons produced a larger range from approximately 31%-37% disagreement. Low variation in conditioning comparisons (Figure 3.4) for each DEM suggests that conditioning method had little impact on derived UCA. Although, lower disagreement percentages were evident when depression filling and stream burning were compared, suggesting greater agreement between the two. However, the stream burning processing methodology also incorporated depression filling to resolve external topographic depressions outside of burned channel networks in the DEM.
The spatial analysis also revealed a significant increase in percent UCA in disagreement for all 1 m LiDAR DEM simulations. This suggests that DEM sensitivity to conditioning technique increases with increasing grid resolution. The effects of depressions on overland flow routing can vary significantly depending on DEM resolution (Lindsay and Creed, 2005). For example, small depressions are easily distinguishable in fine-resolution LiDAR data; however, those depressions are not accounted for in coarser resolutions that generalize topographic features in the landscape (Zhang and Montgomery, 1994). The 1 m LiDAR DEM can easily represent small-scale topographic features that influence overland flow, such as agricultural tillage patterns and road drainage ditches. At finer resolutions, filling techniques remove those features, creating digital ponding that alters natural drainage patterns (Rieger, 1998). Dhun’s (2011) breaching technique accommodates the linear flow features in human-modified landscapes. The disagreement in UCA between filling and breaching techniques is therefore higher in the 1 m LiDAR DEM comparisons because of its ability to model small-scale topographic variation. The stream burning technique performed similarly. The OHN streamline data used to ‘burn’ streams proved highly accurate. Difficulties may arise in stream burning techniques when streamline data varies from the digitally derived stream network, creating parallel stream effects (Callow et al., 2007).

K-S tests for statistical differences in DFL distributions among DEM simulations reveal interesting results. Tests on the 10 m provincial DEM were significant for the depression filling and stream burning comparison and the depression breaching and stream burning comparison (Table 3.6). The 10 m LiDAR DEM tests did not produce statistical significance for any conditioning comparison (Table 3.7). The 5 m LiDAR DEM tests showed significance for the depression filling and depression breaching comparison and the depression breaching and stream burning comparison (Table 3.8). The 1 m LiDAR DEM tests also showed significance for two
comparisons: depression filling and depression breaching and depression filling and stream burning ($p$-values <0.001) (Table 3.9). The two significant 10 m provincial DEM comparisons included the stream burning method. For the two statistically significant 5 m LiDAR DEM simulations, the depression breaching technique was common. Significant 1 m LiDAR comparisons included the depression filling technique. Studies have shown that filling techniques have a greater impact on both the spatial and statistical distribution of terrain attributes when compared to breaching techniques (Lindsay and Creed, 2005; Rieger, 1998). These results do not show one particular technique that is responsible for creating statistically significant differences in DFL distributions, adding to the uncertainty associated with optimal DEM conditioning.

Although the 10 m LiDAR DEM tests showed no statistical significance, the $D_{\text{max}}$ values from the same K-S test ranged from 0.041-0.048. This range of differences was higher than the $D_{\text{max}}$ values for the statistically significant 5 m LiDAR DEM tests. The maximum difference ($D_{\text{max}}$) between DFL distributions may be a more appropriate way to identify differences in the cumulative frequency distributions of hydrological attributes. Similarly to the spatial analysis, differences in DFL distributions vary greatly in the 1 m LiDAR DEM simulations as a result of increased elevation detail due to finer grid resolution. The sensitivity of conditioning techniques to finer-resolution DEMs is clearly evident in the spatial and statistical distribution of UCA and DFL.

### 3.6 Conclusion

Evaluating the effects of DEM grid resolution, elevation source data, and hydrological conditioning techniques on the spatial and statistical distribution of hydrological attributes revealed the following:
DEM grid resolution directly influences the spatial and statistical distribution of derived hydrological attributes. Coarser resolution DEMs resulted in a mixture of larger and severely truncated field sub-basins. The comparison of DFL distributions among DEMs with various resolutions showed statistically significance differences in all cases.

DEM elevation source data directly affects derived hydrological surface derivatives. When compared, the high-density LiDAR data set and the contour-based provincial DEM dataset showed significantly different spatial and statistical distributions of UCA and DFL.

DEM sensitivity to hydrological conditioning techniques increases significantly with DEM grid resolution. Variations in derived hydrological parameters among all conditioning method comparisons increased in the finer resolution LiDAR DEM simulations. The method chosen to hydrologically condition a DEM is highly dependent on the landscape reflected in the DEM and the DEM grid resolution. Therefore, greater consideration of appropriate DEM conditioning methods is required, particularly in research that uses fine-resolution LiDAR DEMs to model hydrological hillslope and field-scale processes.

DEM grid resolution remains a significant determinant of terrain attribute derivation. The use of fine-resolution LiDAR data for advanced hydrological modelling applications is growing in application. Understanding the sensitivity of hydrological surface derivatives to DEM conditioning techniques will be important for future flowpath modelling applications. In addition, a greater understanding of the effects of conditioning techniques on accurate surface and near-surface flowpath modelling will be crucial for studies that incorporate fine-resolution LiDAR DEMs.
Chapter 4.0 Summary and Conclusions

Hydrological modelling applications are highly influenced by DEM data. DEMs are the end result of numerous processing stages that all contain some degree of uncertainty. These uncertainties often determine DEM quality, influence DEM-derived attributes, and determine a level of confidence for numerous modelling applications. A number of studies have explored the effects of DEM elevation source data, interpolation methods, and grid resolutions on derived surface attributes for hydrological applications (Walker and Willgoose, 1999; Wolock and Price, 1994; Zhang and Montgomery, 1994; Lindsay and Creed, 2005). However, researchers have not sufficiently addressed the uncertainties associated with DEM conditioning methods.

Numerous DEM conditioning methods have been developed to resolve flowpaths in places where the topographic information contained in the DEM is insufficient to adequately model pathways, e.g. with topographic depressions and flat areas (Jenson, 1991). Although conventional conditioning techniques remove depression features, they cannot distinguish between actual and artifact depressions. Researchers have found this to be particularly problematic in human-modified landscapes where anthropogenic linear flowpaths alter natural drainage patterns (Duke et al., 2003; Duke et al., 2006). Conditioning directly influences modelled flowpaths and downstream drainage. The development of various DEM conditioning methods has therefore created uncertainty for accurate flowpath determination.

The purpose of this thesis was to assess the impacts of various DEM properties on the spatial and statistical distribution of DEM-derived, field-scale hydrological surface attributes. A case study was performed using DEM data of the Rondeau watershed in southwestern Ontario, where drainage ditches are a major influence in overland flow routing. A total of twelve DEMs were used in this study, each containing various grid resolution, elevation data source, and
applied conditioning technique. Differences in the spatial and statistical distribution of two hydrological properties were examined: upslope contributing area (UCA) and downslope flowpath length (DFL). Results from the case study answered the following research questions:

[1] How does DEM grid resolution influence the definition of field-scale drainage divides and their downslope flowpath length patterns?

DEM grid resolution greatly influences the spatial and statistical distribution of field-scale UCAs and DFLs. Disagreement among derived UCAs was highest between coarse, 10 m LiDAR DEMs and finer, 1 m LiDAR DEMs. Coarser resolution DEMs often resulted in a mixture of larger and severely truncated field sub-basins. Grid resolution was also found to affect cumulative frequency distributions. Statistical differences in DFLs between various DEM grid resolutions confirm the results of Zhang and Montgomery (1994) and Wolock and Price (1994).

[2] How does DEM elevation source data impact field-scale drainage divides and downslope flowpath lengths?

The spatial and statistical distribution of UCAs and DFLs are greatly influenced by DEM source data. Disagreement in derived UCA was high for DEM elevation source data comparisons, indicating that DEM source data is the greatest contributor to differences in the spatial distribution of hydrological parameters when compared to grid resolution or applied conditioning method. Elevation source data also impacted the statistical distribution of DFL distributions. DEMs are commonly limited by their original elevation source data (Walker and Willgoose, 1999; Garbrecht and Martz, 2000). Variations in elevation data collection techniques resulted in notable differences between DEM-derived hydrological attributes.
What are the effects of various DEM conditioning techniques on field-scale drainage divides and downslope flowpath lengths? What are some of the uncertainties associated with DEM conditioning?

The effects of DEM conditioning techniques are closely tied to grid resolution. Differences in the spatial and statistical distribution of UCA and DFL were significantly greater between each conditioning comparison when grid resolution increased. This was particularly evident in the 1 m LiDAR simulations. Greater consideration of DEM conditioning is therefore required at finer-resolutions to ensure the best representation of surface runoff and drainage network configuration.

However, uncertainties still remain regarding optimal DEM conditioning methods. Low variations in the spatial distribution of UCA between conditioning comparisons for each DEM provided no indication of major differences, suggesting similar performances by each technique for all DEM simulations. Similarly, significant differences in the statistical distribution of DFLs among all conditioning comparisons were sporadic. Differences in UCA and DFL showed limited influence from any one particular conditioning method over another. These findings cannot offer a recommendation for a specific conditioning technique that optimizes the accuracy of DEM-derived hydrological attributes.

Overall, this research confirmed the findings of numerous studies that have investigated the effects of DEM grid resolution and elevation source data on derived hydrological attributes. In addition, this research also addressed significant knowledge gaps regarding hydrological DEM conditioning techniques. Conventional DEM pre-processing, prior to hydrological modelling, has strictly removed topographic depressions as a method for drainage enforcement. However, these traditional pre-processing efforts have directly ignored the influence of various DEM conditioning techniques on landscape representation and modelled surface flowpaths. The effects
of various DEM conditioning methods at finer resolutions will be especially significant as LiDAR DEMs continue to appear throughout numerous hydrological modelling applications.

The findings presented in this thesis may be used to advance the current understanding of DEM conditioning techniques and their associated influence on the spatial and statistical distribution of hydrological surface derivatives. In addition, this research may be a useful influence for future studies that seek to identify optimal hydrological conditioning techniques. Optimizing DEM hydrological conditioning will offer significant advancements for DEM quality, influencing modelled water discharge, surface and near-surface flowpath mapping, and predictive environmental modelling applications.
Chapter 5.0 References


Beven, K., and E.F. Wood (1983), Catchment geomorphology and the dynamics of runoff contributing areas, *J. Hydrol.*, 65, 139-158.


Freeman, T.G. (1991), Calculating catchment area with divergent flow based on a regular grid, *Comput. & Geosci.* 17(3), 413-422.


Horton, R.E. (1933), The role of infiltration in the hydrological cycle, *Transactions of the American Geophysical Union* 14, 446-460.


Planchon, O., and F. Darboux (2001), A fast, simple and versatile algorithm to fill the depressions of digital elevation models, *Catena*, 46, 159-176.


