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Quantifying riparian zone structure from airborne LiDAR: Vegetation filtering, anisotropic interpolation, and uncertainty propagation

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SUMMARY

Advances in remote sensing technology, notably in airborne Light Detection And Ranging (LiDAR), have facilitated the acquisition of high-resolution topographic and vegetation datasets over increasingly large areas. Whilst such datasets may provide quantitative information on surface morphology and vegetation structure in riparian zones, existing approaches for processing raw LiDAR data perform poorly in riparian channel environments. A new algorithm for separating vegetation from topography in raw LiDAR data, and the performance of the Elliptical Inverse Distance Weighting (EIDW) procedure for interpolating the remaining ground points, are evaluated using data derived from a semi-arid ephemeral river. The filtering procedure, which first applies a threshold (either slope or elevation) to classify vegetation high-points, and second a regional growing algorithm from these high-points, avoids the classification of high channel banks as vegetation, preserving existing channel morphology for subsequent interpolation (2.90–9.21% calibration error; 4.53–7.44% error in evaluation for slope threshold). EIDW, which accounts for surface anisotropy by converting the remaining elevation points to streamwise co-ordinates, can outperform isoptropic interpolation (IDW) on channel banks, however, performs less well in isotropic conditions, and when local anisotropy is different to that of the main channel. A key finding of this research is that filtering parameter uncertainty affects the performance of the interpolation procedure; resultant errors may propagate into the Digital Elevation Model (DEM) and subsequently derived products, such as Canopy Height Models (CHMs). Consequently, it is important that this uncertainty is assessed. Understanding and developing methods to deal with such errors is important to inform users of the true quality of laser scanning products, such that they can be used effectively in hydrological applications.

1. Introduction

Accurate measurement of surface topography enables quantification of changes in the Earth's surface (Martinez-Casasnovas et al., 2002; Thoma et al., 2005), and in the form of a Digital Elevation Model (DEM), such measurements underpin the numeric simulation of processes that lead to these changes (Bates et al., 2003). In addition to advances in **I**nter**f**erometric **S**ynthetic **A**perture **R**adar (IfSAR; Sanders, 2007), and Aerial Photogrammetry (Lane et al., 2003), airborne **Li**ght **D**etection **A**nd **R**anging (LiDAR) derived data have emerged as a valuable tool for measuring surface topography (Liu, 2008). LiDAR technologies offer the potential to identify 0.5–1 m horizontal scale changes in the Earth's surface elevation and vegetation coverage over regional areas (Arroyo et al., 2010), and also the potential to parameterise regional topography at 0.5–1 m resolution in numerical hydrological/hydraulic models (Bates et al., 2003). In doing so, LiDAR overcomes the temporal and spatial constraints associated with measured topography and vegetation cover in high resolution from ground survey alone (Heritage et al., 2009; Malkinson and Wittenberg, 2007; Raven et al., 2009).

To produce accurate models of surface topography, LiDAR datasets need to be processed through a number of stages (Fisher and Tate, 2006): two critical stages are the removal of non-ground points from the raw data, and interpolation of the remaining ground points. Proprietary filters supplied by contractors to remove vegetation from LiDAR data have been shown to perform poorly in areas of high topographic variability in river channel environments (Bowen and Waltermire, 2002; Bryant and Goodrich, 2005; Faux et al., 2009). Such environments are characterised by steep (and often vertical) channel bank features, which can be obscured by abundant riparian vegetation. A number of studies have shown improved ground point interpolation performance in channel environments when accounting for surface anisotropy (Goff and Nordfjord, 2004; Merwade, 2009; Merwade et al., 2006). The performance of anisotropic interpolation algorithms applied to

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river channels where vegetation cover rather than manual ground survey determines the density of ground point measurements remains uncertain.

A detailed understanding of the errors associated with producing DEMs and Canopy Height Models (CHMs) is required given the potential for error propagation into subsequently derived products; hydrological indices derived from DEMs such as drainage density will be sensitive to these processing stages (Fisher and Tate, 2006; Pirotti and Tarolli, 2010). Further, given strong non-linear relationships between model components and surface topography (Hancock et al., 2010; Horritt et al., 2006; Lane et al., 1999), such errors may propagate into hydraulic and sediment transport models applied using DEM data. Errors may also propagate from a CHM into subsequently derived vegetation metrics, including vegetation biomass, Leaf Area Index (LAI) and carbon storage (Farid et al., 2008; Gonzalez et al., 2010; Hurtt et al., 2004).

Accurate measurement of both surface topography (DEM) and vegetation (e.g. aerial coverage and Canopy Height (Model; CHM)) in river channel environments is required to understand the complex interactions between riparian vegetation, water availability and channel morphology (Atchley et al., 1999; Hereford, 1993; Stromberg et al., 2007), and the impacts of human activities upon riparian ecology (Arroyo et al., 2010).

The research objectives of this study are to: (1) Evaluate the performance of a new non-ground point filter algorithm, specifically designed to remove vegetation from ephemeral channel environments that are characterised by strong topographic variation over spatial scales similar to that of channel vegetation (1–10 m). (2) Evaluate the performance of the Eliptical Inverse Distance Weighting procedure (EIDW) when applied to interpolate elevation in semi-arid channels, where ground-point sampling density is determined by the density and spacing of vegetation patches. (3) Investigate how errors in vegetation filter performance propagates to affect the performance of EIDW employed to reproduce channel morphology.

Section 2 of this paper reviews existing approaches for filtering LiDAR derived data, DEM interpolation, and consideration of error propagation in DEM production. Following a description of the study site and data (Section 3), the new vegetation filter (Section 4) and interpolation procedure (Section 5) are described. Sections 6 and 7, respectively, describe the evaluation procedure and results. Section 8 provides a discussion and Section 9 draws conclusions from the research.

2. Non-ground point filtering, DEM interpolation and error propagation

A significant body of research has investigated both non-ground point removal from LiDAR data, and interpolation of remaining ground-points, either applying both stages together in an iterative procedure (Kobler et al., 2007), or separately (e.g. Cavalli et al., 2008).

Four groups of methods have commonly been classified in the research literature to filter non-ground points from LiDAR derived data: First, interpolation based filters, which include curvature based methods (Evans and Hudak, 2007), and the REIN (**RE**petitive **IN**terpolation) algorithm (Kobler et al., 2007), which by interpolating independent samples of the raw data, generates multiple realisations of the potential ground surface; Second, slope based filters that assume the gradient of the natural terrain is distinct from the slope of non-ground points (Vosselman, 2000; Sithole and Vosselman, 2004); Third, morphological filters that seek to differentiate between ground and non-ground points based on elevation differences between cells in the moving window (Chen et al., 2007; Zhang et al., 2003); and Forth, Segmentation based filters, that apply regional growing and classification rules to segment an image into ground, vegetation or buildings (Nardinocchi et al., 2003).

A number of studies have been conducted to determine the relative performance of different filtering methods (Sithole and Vosselman, 2004; Zhang and Whitman, 2005). Whilst most filters tend to perform well in regions of low complexity such as flat terrain, complex terrains, such as urban areas, steep forested terrain, and river channel areas are more difficult to filter (Faux et al., 2009; Sithole and Vosselman, 2003). Such errors are particularly large when characteristics of the topographic surface traditionally used to discriminate non-ground points (e.g. elevation, first/second derivative of topography) are of similar magnitude to morphological features (Faux et al., 2009). In light of these difficulties a context specific approach to filtering LiDAR data has been recommended (Sithole and Vosselman, 2003).

Methods frequently applied to interpolate ground point data include inverse distance weighting methods (IDW; Burrough and McDonnell, 1998; Lu and Wong, 2008), Spline interpolation (Desmett, 1997), and Kriging methods (Lloyd and Atkinson, 2002). Studies have shown that in areas of low point density, by accounting for trends in spatial structure of data, Kriging outperforms IDW (Lloyd and Atkinson, 2002). However, as LiDAR data in general have high point densities, IDW has been considered an appropriate interpolator of LiDAR data (Liu et al., 2007). Both Liu (2008), and Fisher and Tate (2006) conclude that no single interpolation method is suitable for all terrains and sources of data. In the context of channel environments anisotropic trends in the spatial structure of data need to be considered (Merwade et al., 2006).

Fisher and Tate (2006) argue that relatively little work has investigated error propagation between stages in DEM preparation. Non-ground points that are not filtered from the LiDAR data (Type II errors) may result in erroneous surface morphologies. Similarly, Type I errors may lead to sparse ground points, particularly in areas of high vegetation density, that when interpolated will fail to reproduce surface morphology. There is little guidance in the literature regarding the methods by which parameters (e.g. thresholds and window sizes) incorporated in both stages of DEM preparation have been optimised within any individual test case (e.g. Evans and Hudak, 2007; Zhang and Whitman, 2005). Manual optimisation, as seemingly employed in many studies, may not identify the best DEM surface, nor the optimal parameters, of which there may be many (Beven and Freer, 2001), that may be applied successfully beyond the individual test case. Optimisation and uncertainty quantification methods have been increasingly applied in the hydrological sciences for parameter inference in numerical models (Brazier et al., 2000; Vrugt et al., 2003). Despite the development of these methods, and the widespread use of DEM's in catchment modelling, few studies have applied formal parameter inference to find optimal parameters sets, and understand the sensitivity of DEM accuracy to these parameters (e.g. Kobler et al., 2007).

3. Study location and data acquisition

The Walnut Gulch Experimental Watershed (WGEW) run by the USDA Southwest Watershed Research Service (SWRC) since 1954, is an 150 km^2 experimental catchment located in Southeast Arizona, USA (31° 43′N, 110° 41′W; Renard et al., 2008). The main channel has a complex morphological structure, alternating between weakly braided and single thread sections, and is typical of many rivers in the American Southwest (Pelettier and DeLong, 2004). Between 1974 and 2005 the channel area occupied by vegetation increased by 79% (Nichols and Shipek, 2006), hindering the acquisition of surface morphology from airborne LiDAR.

LiDAR data were obtained by an Optech ALTM 1233 (Optech Incorporated, Toronto, Canada), which was mounted onto a University of Florida plane and flown over the WGEW in the summer of 2003. The Optech ALTM 1233, which has a 1064 nm laser, a