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Terrestrial laser scanning improves digital elevation models and topsoil pH modelling in regions with complex topography and dense vegetation

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ABSTRACT

Terrestrial Laser Scanning (TLS) has great potential in creating high resolution digital elevation models (DEMs). However, little is known about the properties of TLS derived DEMs covering several hectares in heterogeneous environments compared to conventional airborne laser scanning (ALS) based models and their influence on derived products. We investigated the accuracy of DEMs with different resolutions derived from TLS and high quality ALS on a study site with complex micro-topography covered by dense forest and ground vegetation. We further examined the effect of these DEMs on predicted topsoil pH using linear regression models built on terrain attributes. We show that at high resolutions (~1 m), TLS based DEMs performed better than ALS DEMs, which directly translated into significantly better pH models, the best of which showing an R^2 of 0.62. The use of TLS therefore improves the quality of terrain attributes, which are the foundation for many ecological and hydrological applications.

1. Introduction

Digital elevation models (DEMs) are indispensable tools in describing many landsurface forms and processes. They are used in many different fields including hydrological modelling (e.g. Gurtz et al., 1999; Yang et al., 2014) geomorphological (Lin et al., 2013) and digital soil mapping (e.g. McBratney et al., 2003; Nussbaum et al., 2014), natural hazard assessment (e.g. Arnone et al., 2016; Bühler et al., 2015), or ecological species distribution models (e.g. Camathias et al., 2013; Guisan and Zimmermann, 2000). A very widely used source of DEM data is light detection and ranging (LiDAR), a technology which permits creation of high resolution and accurate DEMs (Tarolli, 2014). LiDAR measures the distance between a sensor and a target based on half the elapsed time between the emission of a pulse and the detection of a reflected return (Baltsavias, 1999). Most DEMs derived from LiDAR rely on airborne laser scanning (ALS). ALS surveys are typically designed to have a dense and evenly distributed LiDAR point density over large areas (Bater and Coops, 2009). The accuracy of DEMs generated by ALS is dependent on a range of factors including flight altitude above ground level, flight speed and scan angle (Hyyppä et al., 2008; Maguya et al., 2014). Dense vegetation cover such as multistory forests and dense ground vegetation can reduce the penetration rate of the LiDAR pulses to the ground (Guan et al., 2014; Hodgson et al., 2003; Mulder et al., 2011) and thus also influence DEM accuracy. To derive a DEM, LiDAR reflection points need to be separated into non-ground points, e.g. vegetation returns, and ground points. This can be especially challenging in regions with complex topography and dense vegetation cover, which is often the case in mountainous landscapes (Guan et al., 2014; Maguya et al., 2014; Montealegre et al., 2015). Moreover, several studies have shown that DEM error increases as the ground point density decreases (Anderson et al., 2006; Chu et al., 2014; Jakubowski et al., 2013).

The vertical accuracy of ALS based DEMs in forested and mountainous regions has been assessed in various publications (Bater and Coops, 2009; Kobler et al., 2007; Montealegre et al., 2015). Root Mean Square Errors (RMSEs) of models between 0.16

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and 0.37 m were reported with a point density ranging from 0.7 to 8.5 points/m^2. Bater and Coops (2009) showed that the resolution of DEMs, generated from the same LiDAR ground points, influence DEM accuracy, independently of the applied interpolation method. They created DEMs at spatial resolutions of 0.5, 1.0 and 1.5 m and obtained RMSEs of 0.17, 0.19 and 0.25 m. However, these error values were strongly influenced by the spatial scale of the terrain variation. Cell resolution selection should be based on point density and distribution, horizontal accuracy, terrain complexity (Hengl, 2006) and on the relevant scale for the process or attribute being modeled (Cavazzi et al., 2013; Fisher et al., 2004; Liu, 2008).

The application of terrestrial laser scanning (TLS) has rapidly increased in recent years for purposes including topographical surveys (Gallay et al., 2013), investigations of small scale landslides (Wang et al., 2013) or collecting forest inventory measurements (Dassot et al., 2011; Marselis et al., 2016; Moskal and Zheng, 2011). TLS enables fast and dense height sampling from the surface of objects in the neighborhood of the scanner. The accuracy of these point measurements is in the range of that obtained by a total station. Heritage et al. (2009) reported a median error of −0.003 m for 186 surface points, measured with a total station and a terrestrial laser scanner. TLS is limited to substantially smaller areas than ALS because of the low oblique angle of transmitted signals. In addition, LiDAR impulses can be reflected back to the scanner by obstacles and therefore shadows occur in the 3D point cloud. This is mainly an issue in dense forests with understory and/or areas with a rugged topography (Panholzer and Prokop, 2013). In contrast to ALS which acquires the data at near nadir view angles and thereby yield a relatively homogenous point distribution, TLS generates an irregular distribution of points. The TLS points concentrate around the scanner and density decreases inversely proportional to the square of the distance to the scanner location (Hilker et al., 2010). To mitigate these effects and to generate a 3D point cloud with a larger spatial extent, multiple TLS scans with different viewsheds can be combined in a single dataset. To scan e.g. an area of 60 m^2 in a pine forest for tree canopy studies, 3 scans were required (Danson et al., 2006), whereas 14 scans were taken to survey 36′000 m^2 in a glacial valley to monitor cliff evolution (Heritage and Hetherington, 2007). Due to the irregular point distribution and the shadowing effect of obstacles the separation of ground and non-ground points obtained by TLS is more complex than for ALS data (Panholzer and Prokop, 2013; Rodríguez-Caballero et al., 2016).

So far, relatively few studies have discussed the accuracy of DEMs derived from TLS data and the resulting influence on derived terrain properties. Typically, RMSEs vary considerably depending on the site characteristics. Gallay et al. (2013) compared the accuracy of DEMs derived from TLS data and ALS last return echoes. For a flat terrain with low-cut meadow, the reported RMSEs were 0.007 m for TLS and 0.286 m for ALS data. In an uneven slope covered by dense vegetation the corresponding RMSE were 0.525 m and 0.306 m. However, no filter was applied to separate the point clouds. Pirotti et al. (2013) reported a RMSE of 0.3 m based on DEM composed of 7 scans with a resolution of 0.1 m. The study was conducted in a steep landslide area covered with pioneer species, coppice and tall trees.

For many ecological and environmental models, the spatial distribution of soil properties is a crucial input. To improve e.g. plant species distribution models, accurate and high resolution soil information are considered as a primary requirement (Guisan and Zimmermann, 2000) since the success of a species is largely conditioned by soil chemical properties (Walthert et al., 2013). However, spatially explicit soil data of sufficient quality is scarce, due to the complexity of soil geography and the hidden nature of soil. An added problem are the high costs for soil sampling and for most soil analyses (Rossiter, 2005). In recent years, the spatial availability of soil data has been increased through digital soil mapping (DSM) which has been proven to provide useful soil properties maps (e.g. Samuel-Rosa et al., 2015; Shary and Pinskii, 2013).

Terrain attributes (TAs) such as slope, curvature or topographic wetness index (TWI) act as soil forming factors and thus are related to soil forming processes. They can be derived from DEMs and are often used in DSM as key factors for inferring chemical and physical soil properties (McBratney et al., 2003). Slope and curvature determine the intensity and direction of flows of matter and therefore are relevant for erosion, leaching and accumulation processes (MacMillan and Shary, 2009; Shary and Pinskii, 2013; Wilson, 2012). Similarly, TWI combines upslope contributing area and local slope and is a proxy for soil moisture patterns (Moore et al., 1991; Seibert et al., 2007). The spatial scale of soil forming processes can vary from the very local up to landscape scales, as manifested in the spatial pattern and range of soil properties across a landscape. Therefore, the scale at which these processes operate should determine the optimal scale for deriving TAs (Fisher et al., 2004; Maynard and Johnson, 2014).

The scale-dependency of TAs to spatially predict soil properties suggests that there is an optimal scale to derive TAs for inferring soil properties (e.g. Cavazzi et al., 2013; Kim and Zheng, 2011; Maynard and Johnson, 2014; Pain, 2005; Park et al., 2009; Smith et al., 2006). For topography such as hillslopes, rolling hills, drumlins or dunes, moderate TAs resolutions (15–50 m) produced highest prediction accuracy whereas coarse scaled TAs (>100 m) were most suitable for flat areas. Various recent studies have emphasized that fine-scaled DEMs (resolution < 10 m) are not always the best choice for DSM studies (Cavazzi et al., 2013; Kim and Zheng, 2011; Maynard and Johnson, 2014). Kim and Zheng (2011) argued that soil contains a spatially diffusive nature from one location or grid cell to adjacent locations or cells and therefore edaphic traits (e.g. soil pH, nutrient content) can be influenced by lateral water flow. In a uniform substrate, e.g. sandy dunes, with highly homogenous edaphic conditions the capture of any mircoscale topographic relief is therefore not desirable. In such uniform substrates, fine-resolution TAs might introduce high-frequency noise and do not typically improve spatial predictions (Cavazzi et al., 2013; Kim et al., 2011; Smith et al., 2006). In more rugged areas with a complex substrate structure, by contrast, the fine-resolution TAs are expected to be most suitable for DSM (Kim et al., 2011), who also emphasized that empirical research is needed to test this hypothesis.

To find the appropriate cell size and relevant scale for the process being modeled, a multiscale approach was introduced by Behrens et al. (2010) and Grinand et al. (2008) that incorporates different spatial scales in soil property prediction models. TAs derived from a DEM are smoothed by local average filters with distinct neighborhood sizes to integrate information of the neighborhood into the processed pixel whereas small scale variation is omitted (Liu et al., 2009). Although the scale-dependency of TAs in DSM has been discussed in many publications, the accuracy of different input DEMs in deriving TAs has not been investigated with respect to accuracy of soil properties modelling.

The first aim of this study was to investigate if DEMs derived from TLS data obtained from forested regions with dense vegetation achieve higher accuracies than DEMs based on high quality ALS data. Furthermore, the effect of different resolutions (0.2–4 m) and interpolation methods was addressed and compared with corresponding DEMs derived from ALS data. Secondly, we aimed to evaluate how accuracies and resolutions of DEMs obtained from ALS and TLS data affect the performance of topsoil pH models. For this, we performed a case study in a mountainous, forested site of 2 ha with a strong micro-topography. We derived a set of TAs for