Proceedings, 6th International Conference on Cartography and GIS, 13-17 June 2016, Albena, Bulgaria
ISSN: 1314-0604, Eds: Bandrova T., Konecny M.

A COMPARATIVE STUDY OF CURVATURE AND GRID DATA REDUCTION ALGORITHMS FOR LIDAR-DERIVED DIGITAL TERRAIN MODELS

Mustafa Yilmaz, Murat Uysal

Associate Professor Dr. Mustafa Yilmaz, Department of Geomatics Engineering, Engineering Faculty, Afyon Kocatepe University, Afyonkarahisar, Turkey.

Tel: +90 272 2281423, Fax: +90 272 2281422, E-mail: mustafayilmaz@aku.edu.tr

Associate Professor Dr. Murat Uysal, Department of Geomatics Engineering, Engineering Faculty, Afyon Kocatepe University, Afyonkarahisar, Turkey.

Tel: +90 272 2281423, Fax: +90 272 2281422, E-mail: muysal@aku.edu.tr

Abstract

A digital terrain model (DTM) is defined as the digital cartographic representation of the elevation of the earth's surface created from discrete elevation points. DTMs have been applied to a diverse field of tasks, such as forest management, urban planning, ice sheet mapping, flood control, road design, hydraulic simulation, visibility analysis of the terrain, and topographic change quantification. In parallel with the developments in data processing technologies; satellite remote sensing, airborne laser scanning, and radar interferometry become efficient sources for constructing high quality DTMs in a cost-effective manner. The accuracy of DTM is influenced by several factors such as, the accuracy, the density, and the spatial distribution of elevation points, the terrain surface characteristics, and the interpolation methods. In this study, direct comparisons are made between curvature and grid data reduction algorithms for airborne Light Detection and Ranging (LiDAR) derived DTMs. DTMs with %25, 50 and 75 sampling densities interpolated by the triangulation with the linear interpolation method are compared with the DTM constituted with %100 airborne LiDAR point cloud over the Mount St. Helens in southwest Washington State as the test area. The results show that LiDAR datasets can be reduced to 50% density level by a grid data reduction algorithm while still maintaining the quality of the derived DTM.

Keywords: *DTM, LiDAR, Curvature, Grid, Triangulation with linear interpolation.*

INTRODUCTION

A digital terrain model (DTM) provides a three-dimensional (3D) representation of the bare earth/underlying terrain of the earth's surface that contains elevations of topography (ridgelines, stream courses, breaklines, etc.) where vegetation, buildings, and other non-ground objects have been removed. DTMs have found wide application in all geoinformatics tasks such as: civil planning, mine engineering, military purposes, landscape design, urban planning, environmental protection, forest characterization, hydraulic simulation, visibility analysis of the terrain, surface modelling, topographic change quantification, volume computation, geomorphological extraction, satellite imagery interpretation, cartographic presentation, and geographical analysis (Li et al., 2005). DTMs can be derived by field surveying, photogrammetry or cartographic digitization of existing topographic maps. Compared to the traditional methods for creating DTMs, new technologies such as satellite remote sensing, radar interferometry and airborne laser scanning revolutionize the construction of high quality DTMs in a cost-effective manner. The airborne Light Detection and Ranging (LiDAR) is becoming the privileged data acquisition technique for high-resolution and high-accuracy DTMs over large areas owing to providing 3D non-uniformly spaced dense point information very effectively (Ma and Meyer, 2005; Liu, 2008; Vianello et al., 2009; Razak et al., 2011; Yan et al., 2015). In order to construct DTMs while preserving high frequencies of the relief, the airborne LiDAR has become a well-established resource used to enhance spatial knowledge of the topography.

The airborne LiDAR is an active remote sensing technique providing its own illumination and measures the ranges (variable distances) to the distant objects. The airborne LiDAR sensor sends out light in the form of a pulsed laser and records the energy scattered back from the terrain surface and the objects on the terrain surface. The range is determined by measuring the round trip time between the light emission and the detection of the reflection (Wehr and Lohr, 1999). Each laser pulse may have multiple returns from features hit at different different ranges from the sensor, creating a cloud of geo-referenced points, including buildings and tree canopy, as well as elevations of bare-earth surface points.

The spatial distribution of usable data points is expected to be uniform for DTM construction in a broad application spectrum. Although, the airborne LiDAR have not produced regularly gridded points. The output of the airborne LiDAR survey is a point cloud of hundreds of millions - billions of sample points representing the feature height. Each laser point is randomly located. In many cases, not all points may be required for defining the terrain surface. Therefore, the raw point clouds need to be processed (filtering and interpolation) in order to provide an approximation to a real-world continuous surface (Garnero and Godone, 2013).

The accuracy of the features derived from DTMs depends on several factors originating from: (i) the accuracy, the density, and the spatial distribution of elevation points, (ii) the interpolation methods, (iii) the terrain surface characteristics (Gong et al., 2000; Chen and Yue, 2010; Sailer et al., 2014). There has been extensive literature about these factors: the accuracy of data acquisition (Rayburg et al., 2009; Dorn et al., 2014); the data density (Aguilar et al., 2005; Chaplot et al., 2006); the spatial distribution of source data (Erdogan, 2009; Fassnacht et al., 2014); the interpolation process (Chen and Li, 2012; Arun, 2013); the terrain features (Aguilar et al., 2007; Chu et al., 2014).

The contemporary airborne LiDAR systems can operate between 150.000 to 400.000 laser pulses per second, where achieved density (measurement resolution) exceeds 10 points per square meter (Renslow, 2012). The use of airborne LiDAR has rapidly become a standard source of elevation data for building high quality DTMs. The DTM resolution has increased dramatically in the recent years as a consequence of higher LiDAR point densities. Modern airborne LiDAR sensors allow simultaneously capturing topographic and bathymetric details from large geographical areas at the price of a highly increased data volume. When DTM of different resolution is required the common technique is removing data to produce a coarser resolution data set. Besides, the production of different horizontal resolution DTM from the same data source is important for predicting scale dependent environmental variables. The use of airborne LiDAR offers the flexibility needed to produce multiple horizontal resolutions of DTM from the same data source. However, the high-density LiDAR data lead to a significant increase in the data volume, imposing challenges with respect to data storage, processing, and manipulation for producing DTM. Because of the copious number of LiDAR spot elevations returned on an areal basis, the effects of data density reduction on DTM of various horizontal resolutions is worthy of study, particularly for landscape scale studies. With a data reduction, a more manageable and operationally sized elevation data set is possible (Anderson et al., 2006). Therefore, terrain data reduction (achieving an adjustment between density of data and volume of data) without losing relevant geometric details has become a research topic while constructing DTMs. However, there are particularly limited studies about data reduction for DTMs (e.g., Anderson et al., 2005; Anderson et al., 2006; Liu and Zhang, 2008; Immelman and Scheepers, 2011). The major objectives of this paper are:

- Evaluating the effect of the data reduction algorithms on the accuracy of LiDAR-derived DTM construction.
- Examining to what extent a set of LiDAR data can be reduced while maintaining efficient accuracy for DTM construction.

The results, based on different data densities are compared in terms of the mean error (ME), the mean absolute error (MAE), and the root mean square error (RMSE) with specific reference to a study area.

THEORETICAL BACKGROUND

Data Reduction Algorithms

LiDAR based cloud consist of hundreds of millions - billions of sample points, sometimes, but requires reduction without losing spatial accuracy while constructing DTMs. Through data reduction, manageable dataset, improved efficiency in storage requirements and processing time can be ensured to achieve an operational and efficient DTM. Many algorithms have been proposed to reduce the 3D point cloud data in recent years. A good survey on approaches for data reduction is given in Lee and Jong (2008). It is beyond the scope of this study to discuss even the most common data reduction algorithms in full detail, though the methods and modifications used within this study is provided.

Curvature data reduction (Hamann and Chen, 1994) removes the points based on their curvature. The points are selected with respect to local absolute curvature estimates for piecewise linear curve approximation. The points that lie in high curvature regions are preserved in order to maintain the accuracy of the surface curves. Due to the less detail requirement, the points in flat regions are more likely to be deleted. Grid data reduction (Martin et al., 1996) reduces the number of points in the point cloud by creating evenly spaced set of points, regardless of original density and curvature. A grid structure is built, and the input data points are assigned to the individual grids. From all of the points assigned to a given grid, a median point is selected to represent data points belonging to that cell.

Interpolation Methods

The indispensable data of DTMs are the finite number of sample points, which have horizontal coordinates with uniformly-spaced elevation values. Usually, the spatial distribution of these sample points depends on the source of the data. The digital representation of the terrain surfaces via regular or irregular spaced points is possible by an interpolation method. Several comparative studies have tried to answer the question of an optimal DTM interpolation method, but there is still a lack of consensus about which interpolation method is most appropriate for the terrain data. In this paper, a commonly used interpolation method, Triangulation with Linear Interpolation (TLI) method is chosen.

TLI method creates triangular facets by connecting data points based on an optimal Delauney triangulation. Each triangle defines a plane over the grid nodes lying within the triangle, with the tilt and elevation of the triangle determined by the three original data points defining the triangle. All grid nodes within a given triangle are defined by the triangular surface. Because the original data are used to define the triangles. The result is a patchwork of triangular faces over the extent of the grid. TLI is an exact interpolator that works best when the data are evenly distributed over the grid area (Lee and Schachter, 1980; Webster and Oliver, 2001).

STUDY AREA, DATA ACQUISITION, COMPARISON METHODOLOGY

Mount St. Helens (46°.1912 N, 122°.1944 W) is selected as the study area for the DTM constructions. Mount St. Helens is an active volcano located in Skamania County, Washington, in the Pacific Northwest region of the United States. It is 154 km south of Seattle, Washington, and 80 km northeast of Portland, Oregon. The study area defines approximately area of 116.6 km^2. Its span is ~ 11.9 km in the north-south direction and ~ 9.8 km in the east-west direction.

The comparison process of the DTMs refers to an original LiDAR dataset that consisting of 23071760 points (~ 5.1 m^2/point). The elevation ranges between 743.91 m and 2539.38 m. This variably-spaced bare-earth elevation data set is a portion of a project composed of an area delimited by the 500 year flood plain of the Toutle River, WA river basin (Fig. 1). According to the areas of interest, LiDAR data acquisition specifications are listed below in Table 1.

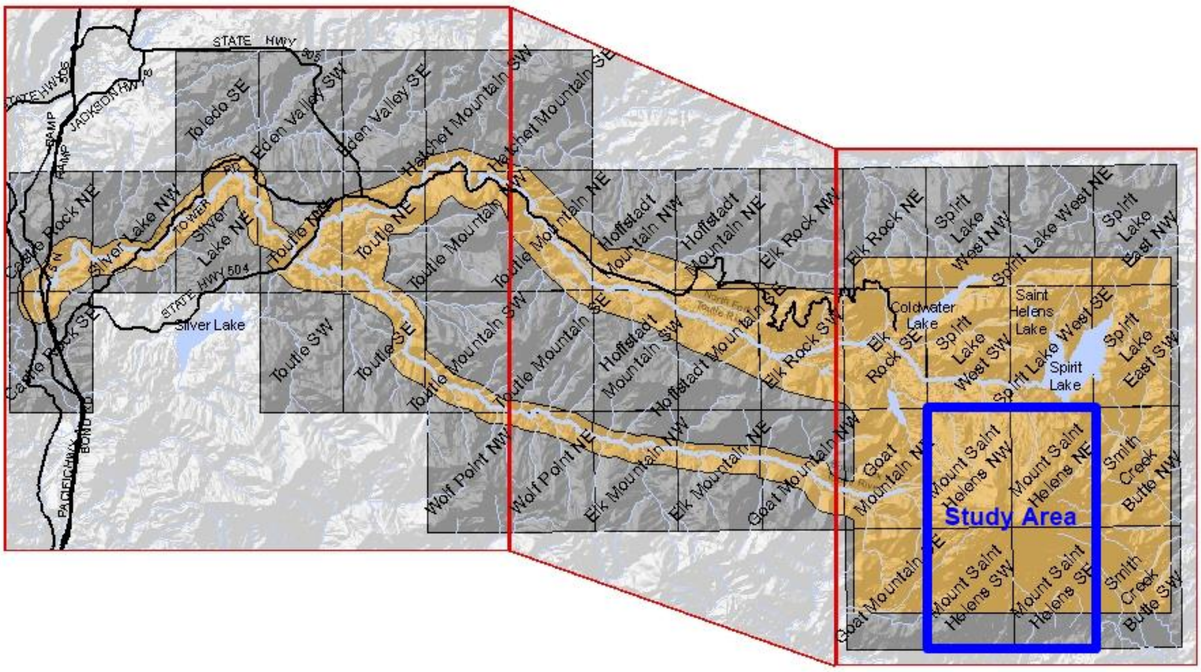

Figure 1. The study area and the coverage of the source LiDAR data

Raw LiDAR elevation points are estimated to be horizontally accurate to 0.30 cm and the vertical accuracies of LiDAR points are within 15 cm. The source LiDAR data set was evaluated against GNSS collected control points which resulted in a vertical RMSE of 0.053 m. LiDAR data were filtered by algorithms within the EarthData's proprietary software and commercial software written by TerraSolid (Mount St. Helens LiDAR Data, 2006).

Table 1. LiDAR data acquisition specifications

	Lower Elevation	Higher Elevation
Flying altitude (m) (above mean terrain)	2133	2438
Flight speed (knots)	140	140
Laser pulse rate (kHz)	29	29
Scan angle (degrees) (from nadir)	± 35	± 35
Scan rate (Hz)	29	18
Swath width (m)	1345	1537

In order to evaluate the effect of the data reduction algorithms on DTM accuracy and to explore the data reduction extent for adequate DTM accuracy; the data density is sequentially reduced through a selection of a predetermined percentage of the original LiDAR data set. Geomagic Studio ® 12 software is used for the data reduction procedure. The original LiDAR data set (100%) is reduced to a series of subsets by using curvature and grid algorithms, representing the 75%, 50%, and 25% of the original LiDAR data set. This reduction protocol is similar to the previous studies of Anderson et al. (2005, 2006). Subsequent to the data reduction, the original LiDAR data set and the reduced data sets are used to produce a series of DTMs. At each data density level, DTMS are constructed via TLI method.

The evaluation of DTM accuracy is focused on the correspondent elevation differences between the reference DTM (based on the original dataset) and the test DTMs (based on the reduced datasets) using the equation below:

$$\Delta Z = Z_{(100\%)} - Z_{(i\%)} \quad (1)$$

where ΔZ is the elevation difference, Z is the elevation value estimated from (reference and test) DTMs, and i represents the data density (i = 75, 50, and 25).

For the statistical analysis of elevation differences, minimum and maximum values of ΔZ are determined and the overall performance of DTMs is assessed through ME, MAE, and RMSE accuracy measures defined by:

$$ME = \frac{1}{n}\sum_{k=1}^{n} \Delta Z \quad (2)$$

$$MAE = \frac{1}{n}\sum_{k=1}^{n} |\Delta Z| \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n} (\Delta Z)^2} \quad (4)$$

where n is the number of the points used for the accuracy verification and k refers to the residual sequence. ME is a measure of underestimation or overestimation the true value of the interpolation method. MAE provides the average deviation that DTM surface deviates from the true value to measure the effect of the data reduction on DTM accuracy. RMSE is calculated to measure the overall accuracy of DTM surface.

COMPARATIVE STUDY

For the comparison process, the reference DTM of the study plotted in Fig. 2, is constructed from the original (100%) LiDAR dataset using TLI method, implemented within the Surfer ® 12 software. All the interpolation methods' parameters (for the reference DTMs) are optimized through cross-validation technique.

The reduced data sets, based on curvature and grid algorithms, are used to construct the test DTMs of the study area using TLI method, at each data density level (75%, 50%, and 25%). The test DTMs ($DTM_{i\%}$; i = 75, 50, and 25) are subtracted from the corresponding reference DTMs ($DTM_{100\%}$) for quantifying elevation differences.

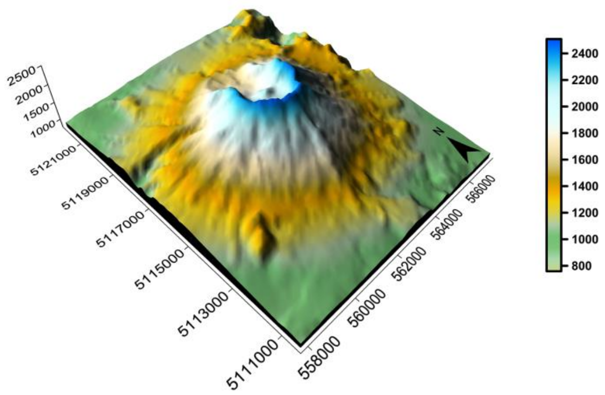

Figure 2. Reference DTM of the study area

The graphical representations have been adopted for the comparative evaluation of the test DTMs by producing a residual map for each test DTM (Fig. 3) that indicates the occurrence and magnitude of elevation differences, in relation to terrain characteristics (by overlaying the contour map of Mount St. Helens on the residual maps).

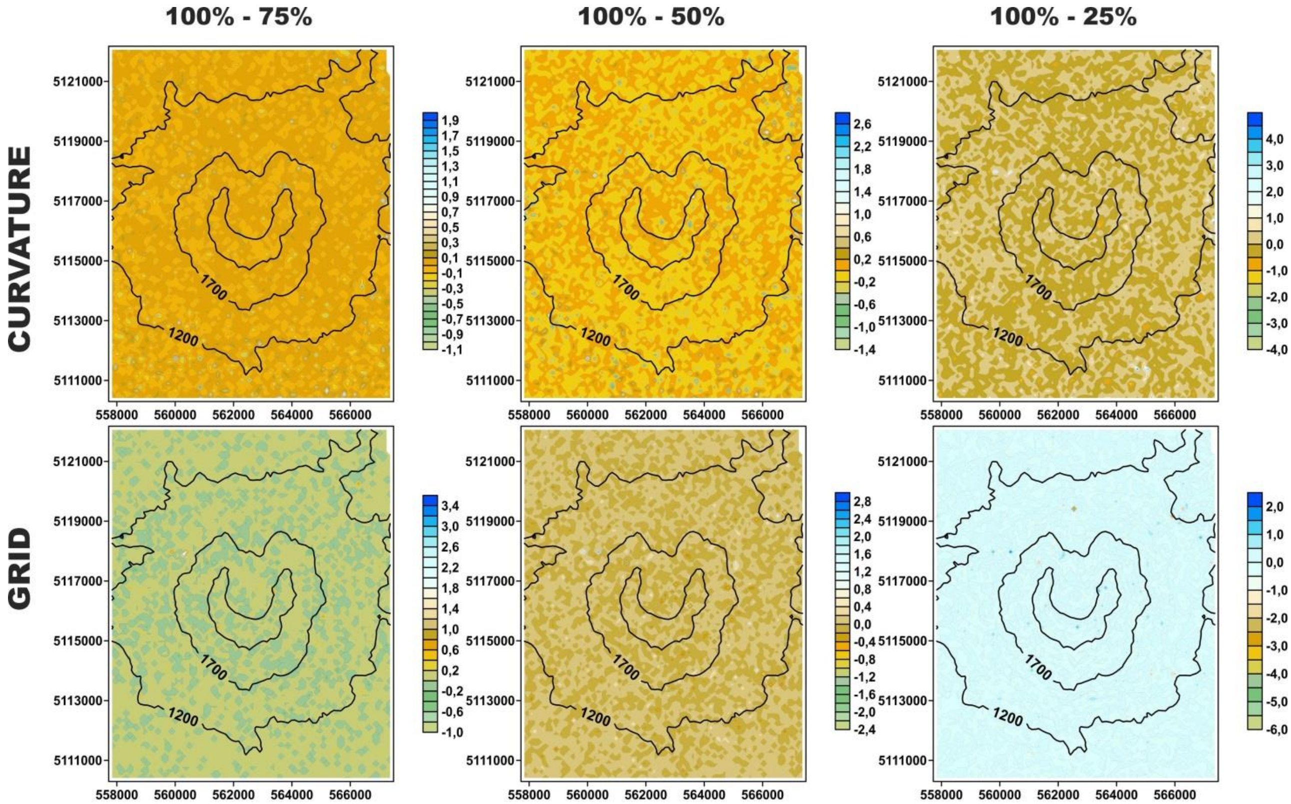

Figure 3. Residual maps of test DTMs for the study area

RESULTS AND CONCLUSIONS

The visual analysis of the elevation residual maps (Fig. 3) indicates that the deviation of the test DTMs from the

reference DTM is getting greater depending on the decreasement of data density, for curvature and grid data reduction algorithms. The thorough visual interpretation of the elevation residual maps reveals better results of grid algorithm than curvature algorithm.

The statistics of elevation residuals based on curvature and grid algorithms at selected data density levels are presented in Table 2, and the relevant MEs, MAEs, and RMSEs are graphically represented in Fig. 4. When the statistics summarized in Table 2 are evaluated, it can be seen from Fig. 4 that grid algorithm provides more accurate results than curvature algorithms at every data densities.

Table 2. The statistics of the elevation residuals (units in m.)

	CURVATURE			GRID		
	75%	50%	25%	75%	50%	25%
Min	-1.052	-1.337	-3.882	-0.984	-2.303	-5.867
Max	1.847	2.510	4.394	3.301	2.730	1.933
ME	0.001	-0.004	-0.014	0.000	-0.003	-0.005
MAE	0.037	0.093	0.176	0.024	0.059	0.119
RMSE	0.091	0.170	0.307	0.082	0.126	0.212

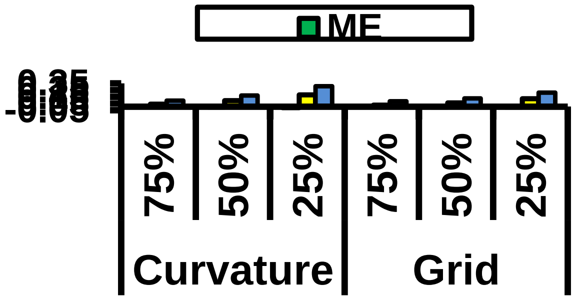

Figure 4. The accuracy measures of the elevation differences (units in m.)

MEs are recorded at the centimetre level at 25% data density for curvature and grid data reduction algorithms (-0.005 m. and -0.014 m.). TLI underestimated the terrain surface because of the predominantly concentric topography of the study area. MEs are sub-centimeter at 50% and 75% data densities for curvature and grid data reduction algorithms, indicating that interpolation biases were negligible.

Throughout the decreasing data densities, the test DTMs have increasing MAEs ranging from 0.024 m to 0.176 m. Terrain representations derived from the test DTMs based on grid algorithm are better than the test DTMs based on curvature algorithms, at all data densities.

RMSEs ranged from 0.082 m. to 0.307 m. show significant increases for curvature and grid data reduction algorithms as data densities decreased from 75% to 25%. As expected, the lowest RMSEs are obtained at 75% data density level. RMSEs of the test DTMs for data reduction algorithms have a decreasing sequence as grid < curvature, at all data densities.

In terms of overall accuracy, there is no significant decrease for the test DTMs constructed from high data densities (75% and 50%) (Fig. 4). Hence, it becomes apparent that the test DTMs based on 75% and 50% point densities are sufficient for terrain representations.

Based on the analysis results of comparison of data reduction algorithms in constructing DTMs, the following conclusions can be drawn based on this paper: (i) Grid data reduction algorithm can be considered as a feasible technique due to better terrain representation for constructing LiDAR-derived DTMs. (ii) TLI biases are negligible with lower RMSEs in terms of grid data reduction approach at higher data densities (75% and 50%). (iii) LiDAR datasets can be reduced to 50% density level while still maintaining the DTM accuracy.

The airborne LiDAR is one of the most capable, effective, and reliable tool for gathering high-accuracy and high-density 3D terrain data leading to mapping products. The limitations of the use of LiDAR data in constructing DTMs are the magnitude of data and the intense post-processing. However, high-density data associated with LiDAR lead to imposing challenges with respect to data storage, processing and manipulation. Large data volumes obtained from LiDAR often require data reduction without losing relevant geometric details while constructing DTMs because the quality of LiDAR-derived DTMs equates to how well it represents the terrain undulation and continuity. The results of this paper show that grid algorithm is useful for data reduction due to its lower RMSEs. The data should be reduced by keeping critical data (considering terrain features). Due to the required DTM accuracy, extensive attention should be paid to reducing LiDAR data without extraction critical terrain elements. In order to represent the terrain morphology with the reduced data, future researches using diverse data reduction algorithms are necessary to determine the effective data reduction algorithm and the threshold data density for constructing DTMs.

REFERENCES

Aguilar, F.J., Agüera, F., Aguilar, M.A., Carvajal, F. (2005). Effects of terrain morphology, sampling density and interpolation methods on grid DEM accuracy. Photogrammetric Engineering and Remote Sensing, 71 (7), 805-816.

Aguilar, F.J., Aguilar, M.A., Agüera, F. (2007). Accuracy assessment of digital elevation models using a non-parametric approach. International Journal of Geographical Information Science, 21 (6), 66-686.

Anderson, E.S., Thompson, J.A., Austin, R.E. (2005) LIDAR density and linear interpolator effects on elevation estimates. International Journal of Remote Sensing, 26 (18), 3889-3900.

Anderson, E.S., Thompson, J.A., Crouse, D.A., Austin, R.E. (2006) Horizontal resolution and data density effects on remotely sensed LIDAR-based DEM. Geoderma, 132 406– 415.

Arun, P.V. (2013). A comparative analysis of different DEM interpolation methods. The Egyptian Journal of Remote Sensing and Space Sciences, 16, 133-139.

Chaplot, V., Darboux, F., Bourennane, H., Leguédois, S., Silvera, N., Phachomphon, K. (2006). Accuracy of interpolation techniques for the derivation of digital elevation models in relation to landform types and data density. Geomorphology, 77, 126-141.

Chen, C.F., Yue, T.X. (2010). A method of DEM construction and related error analysis. Computers and Geosciences, 36 (6), 717-725.

Chen, C., Li, Y. (2012). A robust method of thin plate spline and its application to DEM construction. Computers and Geosciences, 48, 9-16.

Chu, H.J., Chen, R.A., Tseng, Y.H., Wang, C.K. (2014). Identifying LiDAR sample uncertainty on terrain features from DEM simulation, Geomorphology 204, 325-333.

Dorn, H., Vetter, M., Höfle, B. (2014). GIS-based roughness derivation for flood simulations: a comparison of orthophotos, LiDAR and crowdsourced geodata. Remote Sensing, 6, 1739-1759.

Erdogan, S. (2009). A comparison of interpolation methods for producing digital elevation models at the field scale. Earth Surface Processes and Landforms, 34 (3), 366-376.

Fassnacht, F.E., Hartig, F., Latifi, H., Berger, C., Hernández, J., Corvalán, P., Koch, B. (2014). Importance of sample size, data type and prediction method for remote sensing-based estimations of aboveground forest biomass. Remote Sensing of Environment, 154, 102-114.

Garnero, G., Godone, D. (2013). Comparisons between different interpolation techniques. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. XL-5/W3, 139-144.

Gong, J., Li, Z., Zhu, Q., Sui, H., Zhou, Y. (2000). Effects of various factors on the accuracy of DEMs: an intensive experimental investigation. Photogrammetric Engineering and Remote Sensing, 66 (9), 1113-1117.

Hamann, B., Chen, J.L. (1994). Data point selection for piecewise linear curve approximation. Computer Aided Geometric Design, 11, 289-301.

Immelman J., Scheepers L.G.C. (2011). The effects of data reduction on LiDAR-based digital elevation models, 4th International Congress on Image and Signal Processing, Shanghai, China, 1694-1698.

Lee, D.T., Schachter, B.J. (1980). Two algorithms for constructing a Delaunay triangulation. International Journal of Computer and Information Sciences, 9 (3), 219-242.

Lee P., Jong B. (2008). Point-based simplication algorithm. WSEAS Transactions on Computer Research, 1, 61-66.

Li, Z., Zhu, C., Gold, C. (2005). Digital Terrain Modeling: Principles and Methodology. Boca Raton: CRC Press.

Liu, X. (2008). Airborne LiDAR for DEM generation: some critical issues. Progress in Physical Geography, 31 (1), 31-49.

Liu, X., Zhang, Z. (2008). LiDAR data reduction for efficient and high quality DEM generation, The International Archives of the Photogrammtery, Remote Sensing and Spatial Information Sciences, XXXVII, 173-178.

Ma, R., Meyer, W. (2005). DTM generation and building detection from LiDAR data. Photogrammetric Engineering and Remote Sensing, 71, 847-854.

Martin, R.R., Stroud, I.A., Marshall, A.D. (1996). Data reduction for reverse engineering, RECCAD, COPERUNICUS project, No. 1068, Computer and Automation Institute of Hungarian Academy of Science.

Mount St. Helens LiDAR Data (2006). https://wagda.lib.washington.edu/data/type/elevation/lidar/st_helens/ (Accessed 04 April 2016).

Rayburg, S., Thoms, M., Neave, M. (2009). A comparison of digital elevation models generated from different data sources. Geomorphology, 106, 261-270.

Razak, K.A., Straatsma, M.W., van Westen, C.J., Malet, J.P., de Jong, S.M. (2011). Airborne laser scanning of forested landslides characterization: Terrain model quality and visualization. Geomorphology, 126, 186-200.

Renslow, M.S. (2012). Introduction. In M.S. Renslow (Ed.), Manual of Airborne Topographic LiDAR (pp. 1-5). Bethesda: ASPRS.

Sailer, R., Rutzinger, M., Rieg, L. Wichmann, V. (2014). Digital elevation models derived from airborne laser scanning point clouds: appropriate spatial resolutions for multi-temporal characterization and quantification of geomorphological processes. Earth Surface Processes and Landforms, 39 (2), 272-284.

Vianello, A., Cavalli, M., Tarolli, P. (2009). LiDAR-derived slopes for headwater channel network analysis. Catena, 76 (2), 97-106.

Webster, R., Oliver, M. (2001). Geostatistics for Environmental Scientists. Chichester: John Wiley and Sons.

Wehr, A., Lohr, U. (1999). Airborne laser scanning-An introduction and overview. ISPRS Journal of Photogrammetry and Remote Sensing, 54, 68-82.

Yan, W.Y., Shaker, A., El-Ashmawy, N. (2015). Urban land cover classification using airborne LiDAR data: A review. Remote Sensing of Environment, 158, 295-310.

BIOGRAPHIES

Mustafa Yilmaz received the B.Sc. degree (1999) in Geodesy and Photogrammetry Engineering from Selcuk University of Konya, Turkey and the M.Sc. degree (2002) in Geodesy from the same university. He received the Ph.D. degree (2012) in Geodesy from Afyon Kocatepe University of Afyonkarahisar, Turkey. He is currently working as an Associate Professor in the Geomatics Engineering Department of the same university. His research interests are geopotential models, geoid determination, Earth crustal velocity, digital terrain models, and artificial neural networks.

Murat Uysal received the B.Sc. degree (1995) in Geodesy and Photogrammetry Engineering from Selcuk University of Konya, Turkey and the M.Sc. degree (1999) in Photogrammetry from Afyon Kocatepe University of Afyonkarahisar, Turkey. He received the Ph.D. degree (2009) in Photogrammetry from Yildiz Technical University of Istanbul, Turkey. He is currently working as an Associate Professor in the Geomatics Engineering Department of Afyon Kocatepe University of Afyonkarahisar, Turkey. His research interests are remote sensing, laser scaning, 3D modelling, and LiDAR measurements.