Can binning be the key to understanding the uncertainty of DEMs?

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1. Introduction

Digital elevation models (DEMs) have been a subject of intensive interest within the geographical information science community for several decades now. The fundamental reason for the interest is the wide range of DEM uses and applications (for a review, see, e.g., Oksanen 2006), but the recent boom in DEM-related research can be explained by the breakthrough of airborne laser scanning (ALS). ALS is a remote sensing method based on Light Detection and Ranging (LIDAR), in which the Earth's surface is illuminated from an aircraft with a laser, backscattered radiation is recorded with a photodiode and a GPS/Inertial Measurement Unit (IMU) is used to define the location of each reflected laser pulse (Hyyppä et al. 2008).

Similar to the interest in DEMs in general, the scientific community has put significant effort into understanding the uncertainty of DEMs. These studies may be roughly divided into two groups. One perspective emphasizes DEM quality as an intrinsic and generic value (e.g. Torlegård et al. 1986, Li 1993, Kumler 1994, Carrara et al. 1997, Weng 2002, Hodgson et al. 2005, Ahokas et al. 2008, Aguilar et al. 2010), while the other perspective sees the DEMs as input data for a particular model and the interest has to do with the influence of DEM uncertainty in the modelling process (e.g. Fisher 1991, Heuvelink 1998, Kyriakidis et al. 1999, Oksanen 2006). Unfortunately, any sort of convergence between these two perspectives has been quite limited and even a diffusion of the earlier findings, such as the spatial nature (Fisher 1998) and non-stationarity (Oksanen & Sarjakoski 2010) of the DEM error, has been unexpectedly slow (Table 1). Even though some mapping agencies recognise the spatial variation in DEM quality (e.g. LM 2012, Swisstopo 2012), the standard for geospatial data quality (ISO 2006), for one, ignores the spatial nature of the DEM error and declares that the height can be treated as a one-dimensional random variable.

This paper focuses on one interesting phenomenon found in a number of DEM quality studies – the apparent non-normality, or leptokurtosis, of the DEM error distribution (e.g. Bonin and Rousseaux 2005, Oksanen & Sarjakoski 2006, Aguilar 2007, Zandbergen 2011, Wise 2011, Mudron et al. 2012) and how binning, i.e. the grouping of data, could be used to understand the phenomenon. Here, the term error is used to refer to the elevation difference between the DEM and the reference measurement, while the standard error is the parameter characterizing the whole distribution of errors, as measured by the standard deviation or root-mean-square error (RMSE). The earlier research on vertical error in DEMs suggests a number of explanations for the non-normality of the error distribution: 1) the frequent occurrence of gross errors or blunders, 2) the large positive autocorrelation of the vertical error in DEMs, and 3) the non-stationary processes underlying the occurrence of vertical errors in DEMs (e.g. Zandbergen 2011). This paper attempts to find a connection between the non-normality and non-stationary processes influencing the DEM uncertainty. Yet, have we overlooked the possibility that the error pattern that we see globally is actually a combination of a number of overlapping local random processes? This idea has been presented earlier (Oksanen & Sarjakoski 2006), but the explanation for the phenomenon has remained hidden.

Table 1. Examples of LIDAR DEM quality statements cited from selected European national mapping agencies

DEM product	Producer	Quality statement
DEM2	National Land Survey of Finland	"…the accuracy of height data 0.3 metres." (NLS 2012)
Landform PROFILE® Plus	Ordnance survey (UK)	"Vertical accuracy (RMSE): 0.25 m or better" (OS 2012)
GSD-Elevation data, grid 2+	Lantmäteriet (Sweden)	"The accuracy of the individual laser points is usually better than 0.1 metres on flat, paved surfaces. Locally, however, the accuracy may be significantly less, e.g. in areas with a steeply sloping terrain or an indistinct ground level. Moreover, in areas with a dense forest the point density will be lower, which means that small terrain formations may be lost." (LM 2012)
DOM GRID 2 m	Swisstopo (Switzerland)	"Accuracy: In open terrain: ±0.5 m 1σ, In terrain with vegetation: ±1.5 m 1σ" (Swisstopo 2012)

2. Materials and methods

The NLS DEM2 that was tested and the NLS LIDAR point cloud that was used to create the NLS DEM2 were freely available from the NLS's downloading service (Table 2). The complete reference dataset contained four, approximately 7.5 km long, LIDAR control strips (flying altitude 500 m, strip width ca. 180 m) taken from the FGI's Nuuksio test environment (Sarjakoski et al. 2007), of which only one flight line's ground points were used in this study.

Table 2. Datasets used in the study

	Elevation datasets		
Data	NLS DEM2	NLS LIDAR point cloud	FGI LIDAR point cloud
Producer	National Land Survey of Finland	National Land Survey of Finland	Finnish Geodetic Institute
Scanning date	-	May 2008	June 2007
Flying altitude	-	2000 m	500 m
Average point density	-	0.56 pnt/m^2	12.25 pnt/m^2
N points	-	602 942	13 216 449
Grid size	2 m	-	-
Purpose	Calculation of response variable (RMSE)	Derivation of predictor variables	Reference data

Before calculating the elevation differences between the NLS DEM2 and the reference data, the ellipsoidal heights of the reference data were adjusted to the N2000 elevation system used in NLS DEM2 (JHS 2008). The predictor variables (Table 3) used for binning and modelling the NLS DEM2's RMSEs were calculated either by using the NLS DEM2 directly or by using the NLS LIDAR point cloud, from which all of the overlaps of adjacent flight lines were removed. For calculating the global RMSEs, extreme outliers (Milton & Arnold 1995) were removed from the whole data, whereas for the local binned analysis they were removed from each bin.

Table 3. Predictor variables used for binning the elevation differences (NLS DEM2 - reference data)

Predictor variable	Input data	Calculation method	Unit
Slope	NLS DEM2	Third-order finite-difference method (Horn 1981) in a 2 m grid	%
Vegetation density	NLS point cloud	Number of points in a vegetation class in a 5 m grid => Coverage of cells having more than 5 points in a 10 m radius calculation window	%
Scanning angle	NLS point cloud	Point-wise scanning angle => TIN	°
Ground point density	NLS point cloud	Average ground point density in a 5 m grid	pnt/m^2

3. Results

The global RMSE of the NLS DEM2 was 0.11 m when ignoring all of the location-dependent effects. Prior to further analysis, the co-variation of the predictor variables was checked to guarantee that the similarity between the bins has been minimized in the following binning steps (Figure 1). The only statistically significant moderate negative correlation was found between vegetation and the ground point density, as was expected.

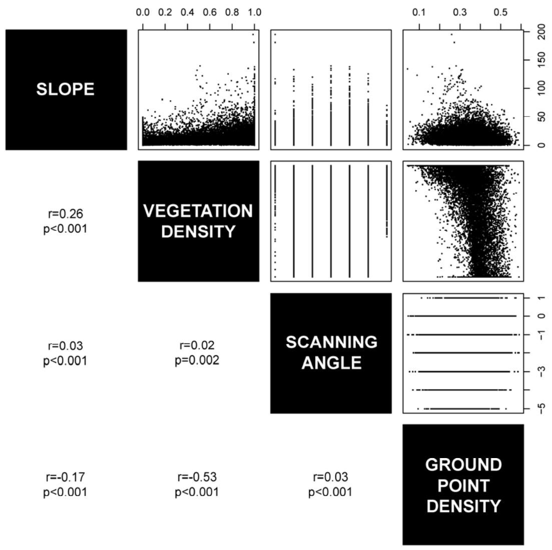

Figure 1. Co-variation and Pearson's product-moment correlation coefficients (r) of the predictor variables

When the RMSE of the NLS DEM2 was analyzed separately for each bin of predictor variables, it revealed that the DEM error appeared to be a combination of a number of overlapping random processes (Figure 2). The associations between all of the predictor variables and RMSEs were as expected: steep slopes, high vegetation density, large scanning angles and low ground point densities explained the high RMSEs. The RMSEs varied as much as 0.08–0.56 m between the slope bins, while the range of variation in the other predictor variable bins were approximately 0.05 m. When these RMSE values are compared with the global RMSE, we find that the global RMSE appears to overestimate the error in areas of flat and open terrain, when observed with small scanning angles, and underestimates the error in the other areas. Further inspection of the histograms and regression curves reveals that the majority of the study area is flat terrain with a low RMSE, whereas very small areas have steep slopes and a high RMSE. When this type of error distribution originating from a number of overlapping random processes is inspected globally, we see a similar leptokurtic distribution as in a number of earlier studies (e.g. Bonin & Rousseaux 2005, Oksanen & Sarjakoski 2006, Zandbergen 2011, Wise 2011, Mudron et al. 2012).

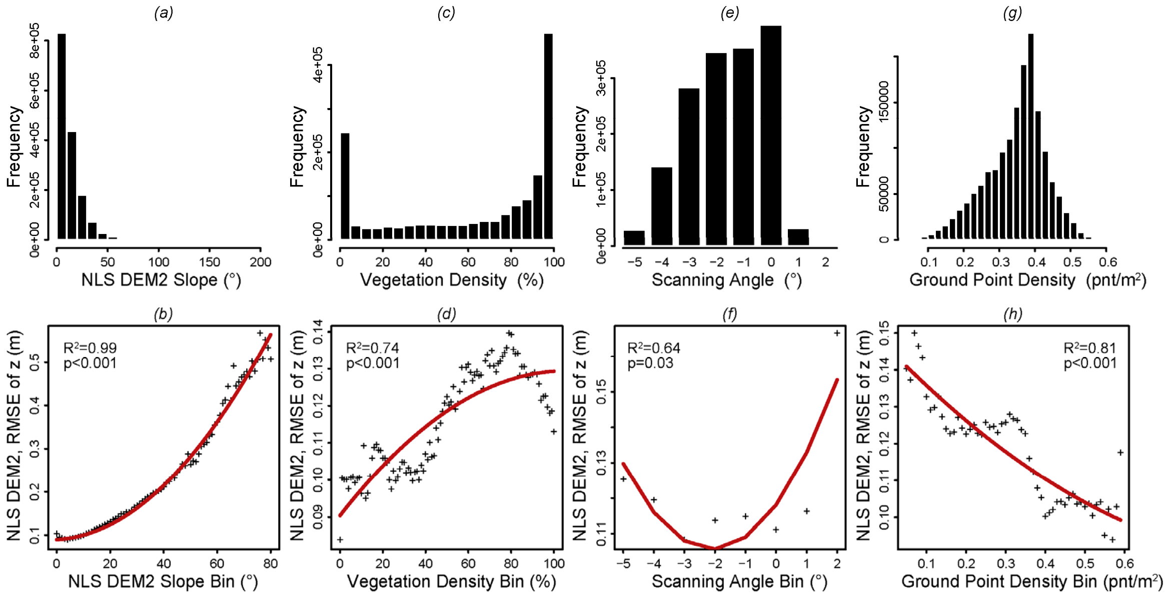

Figure 2. Histograms of the predictor variables in the study area (a, c, e and g), RMSE's of the NLS DEM2 elevations calculated for each predictor variable bin, and regression curves modelling the effect of the predictor variable on the NLS DEM2's RMSE (b, d, f and h).

4. Conclusions and future work

The study showed the importance of taking the non-stationary effects of DEM uncertainty into account in accuracy assessment, as well as in error models created for uncertainty-aware terrain analysis. In particular, the dominating slope effect must not be ignored due to its high range, almost 0.5 m. These effects become visible by applying a binning approach, but feasibility of other modelling methods, such as geographically weighted regression (Brunsdon et al. 1996), allowing inclusion of non-stationary effects should be evaluated.

When these findings are further elaborated and validated by analysing all of the control strips, the implications of the study might be far reaching. First, we should no longer report on DEM quality using only single dispersion statistics. Second, the use of conventional geostatistics directly when observing the elevation differences in DEM error propagation studies may now be questioned, because the error pattern we see appears to be a combination of a number of overlapping random processes and the overlapping effects should be removed from the data before the use of geostatistical tools. Finally, since the non-stationary effects, especially the slope effect, have a major influence on the uncertainty statistics, the phenomenon must not be ignored in the sampling design for the reference data. The reference data must be representative, but it must represent all of the significant random processes found in the study area.

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Biography

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