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Using geographically weighted regression for analysing elevation error of detailed digital elevation models

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Abstract

This case study concerns vertical errors of five different high-resolution digital elevation models (DEMs) originated from light detection and ranging (LiDAR), interferometric SAR (InSAR) and photogrammetric acquisition. The LiDAR DEM derived from last return points was considered as the reference DEM. The aim was to analyse the statistical and spatial distribution of the residuals and their relationship with the DEM surface roughness of the analysed DEMs. Surface roughness measured as area ratio and inverted vector strength were used to parameterise the DEM surface. The results show that globally no linear relationship exists between the surface roughness and DEM residuals but it was found to be very diverse locally. High elevation errors occurred along DEM artefacts and sharply defined landforms. The applied surface roughness parameters were found to be useful predictors of such features and could be used for identification of such features.

Keywords: GWR, DEM error, LiDAR, roughness, local analysis
Klíčová slova: geograficky vážená regresie, DMR, lokální analýza, LiDAR

1. Introduction

Much work has been expended on developing digital representations of the Earth's surface. Digital elevation models (DEMs) as regular grids of values are the most widely used forms of such representations. Nation-wide detailed DEMs were traditionally generated of data acquired by photogrammetry or digitizing topographic maps. The advance of technology in the last two decades enabled highly accurate data collection by laser detection and ranging (LiDAR) and interferometric SAR (InSAR). The methods used for elevation data acquisition and processing have a marked impact on the quality of derived DEM and other parameters of the DEM surface (Wilson and Gallant, 2000, Hengl and Reuter, 2008). For that reason, the accuracy of how well the digital representation approximates the real earth surface is of principal interest for academics as well as practitioners.

Vertical accuracy of DEM (DEM error) has long been the most widely used measure of DEM quality. Vertical errors are typically calculated as residuals (differences) between the validated DEM data points and a more accurately measured sample. The mean error (ME) and root mean squared error (RMSE) are the standard measures of DEM accuracy. However, many recent studies recognize the need for more diverse parameterisation of DEM quality. DEM derived data became an assessment tool rather than just a product of geomorphometric analysis (Chaplot et al. 2006, Fisher and Tate, 2006). In order to understand and predict the errors, researchers attempted to quantify the error distribution and identify relationship with the surface properties such as slope angle, slope aspect or curvature (Gao 1997, Wise 2008, Erdogan, 2010). Another approach of DEM error modelling involves stochastic simulation of the error field assuming its distribution is normal Gaussian and stationary parameterised by the ME and RMSE.

1.1 Two types of DEM error

One can distinguish two basic approaches for DEM error calculation. The first comprises residuals based on a single dataset split into two parts one of which is used for DEM production while the other is not used and remains for validation of the DEM. Cross-validation, or jack-knifing are examples of such a technique. The errors can be regarded as measures of robustness or reliability of the spatial prediction with respect to the input data rather than the accuracy or a goodness-of-fit of the DEM to the real topography. Desmet (1997), Wise (2008) or Erdogan (2010) conducted such assessment and found significant correlation of DEM vertical errors and DEM geomorphometric parameters. The findings were based on differences between a high-resolution DEM and the DEM interpolated to coarser resolutions. However, the RMSE reflected DEM error of the resampled DEM versions with respect to the source DEM and, although useful, it does not suggest much about the RSME measured with respect to a more precisely measured set of elevations. This represents another approach of DEM error calculation traditionally done by taking a relatively small number of more accurate reference observations with respect to a large number of cell values comprising the evaluated DEM. The limited number of reference sample constrained the characterisation of the DEM error to global summary statistics such as mean error and RMSE. In order to model the DEM error for each data point of the tested DEM the measures are used to parameterise the statistical distribution of the error and an assumption was accepted that the distribution is normal and stationary. It was recognised that a more realistic approach of DEM error modelling is to assume spatially autocorrelated error field (Hunter and Goodchild 1997, Wechsler and Kroll 2006). The advance of rapid acquisition by LiDAR provided sources of dense and highly accurate coverage of elevation data points which can be regarded as the most realistic and more accurate representation of the real earth surface. The data are available as reference points for every location of the assessed DEM given the spatial resolution of the validated DEM dataset is the same or lower. This potential of LiDAR data is explored in the paper.

1.2 Local analysis of DEM error

It is generally accepted that the measurement errors are not spatially random but a relationship exists with surface geometry. Quantifying the relationship is useful for the purposes of error modelling and propagation and has been the focus of research for more than a decade. The error distribution can be described by local indicators of spatial analysis as proposed in Anselin (2003). Variograms, Moran's I or Getis' C are the most popular (Lloyd, 2006). Ordinary least squares (OLS) linear regression or its logarithmic variants are generally used to define the relationships. These can be considered as global approaches which indicate trend for the entire population not considering geographical location. However, the correlation between the morphometric parameter and DEM error can be stronger in some places and weaker in others, or it can be positive or negative locally. In such cases, approaches which take geographical location into account and adapt regression parameters can be used to improve the understating between two variables. Geographically weighted regression (GWR) is one of the most recent tools for local regression especially popular in social and economic geographic studies. The technique is described in detail by its developers in Fotheringham et al. (2002). Carlisle (2005) used OLS for DEM error modelling noting that GWR could improve the predictions if a larger reference dataset is used. Erdogan (2010) conducted such GWR modelling of error of interpolated DEM from levelling data. The errors were the product of a jack-knifing procedure of DEMs interpolated to coarser resolutions.

This paper uses a similar framework as presented in Erdogan (2010) but LiDAR data are used as the reference sample. The data are sampled on a similar sampling density as the evaluated DEM. It was assumed that inference based on such error field keeping the working scale constant provided a more realistic picture of the DEM quality and so improves its understanding.

2. Study site and data

The datasets used for the research cover an area of the Great Langdale Valley in the Lake District, Cumbria, England. The site is approximately 1500 by 1500 metres in extent and was chosen due to its considerable variation of terrain and spatial overlap of diverse ready-to-use commercial DEMs. The DEM data were generated from data collected by airborne remote sensing with the stated vertical accuracy and sampling density as follows: LiDAR (0.25 m, 2 m), InSAR (1 - 2.5 m, 5 m), photogrammtery (1.5 m, 10 m) and digitized contour lines (2.5 – 5 m, 10 m). All datasets were digital representations of the terrain surface ('bald earth', DTM) except the InSAR data of which both terrain and topographic surface models were provided (DSM). All the data sets are proprietary DEM products provided as fine resolution grids, except the LiDAR points, projected in the OSGB36 coordinate system. The spatial resolution of each DEM type was almost identical to its sampling density, but different between the DEM types. For the purposes of this study the data were considered comparable after they were resampled to 5 metre grids which refers to working scale about 1:10 000. The DEMs thus comprised about 81 000 cell values.

3. Methods

A reference DEM (DEMREF) was interpolated from the LiDAR points of last return (ca. 2 m spacing) with inverse distance weighting and the cell-size of 5 metres to match the resolution of the resampled DEMs. The rationale for the interpolation of the relatively dense field of LiDAR points was to estimate the elevation exactly on locations of the observed values which were the centres of grid cells of the resampled DEMs. The DEMREF was subtracted from the other four DEMs (InSAR DSM, InSAR DTM, Photog. DTM, Cont. DTM). (Residuals DEM = DEM – DEMREF). Thus, the difference surfaces of the same spatial resolution were generated. The DEM residuals were masked on locations where above-ground surface objects were present (Fig. 1 C). Subsequently, statistical and spatial distribution of the DEM residuals was characterised by global summary statistics and measures of spatial autocorrelation which are presented in Tab. 1.

Tab. 1. Summary statistics of the DEM residuals.

DEM type	1st Quartile *	Median *	3rd Quartile *	Mean *	Standard deviation *	RMSE *	Moran's I	Moran's I z-score
InSAR DSM	-0.86	-0.26	0.35	0.05	3.66	3.66	0.83	2.34
InSAR DTM	-1.15	-0.30	0.48	-0.09	3.67	3.67	0.91	2.58
Photog. DTM	-1.29	-0.21	0.90	-0.38	2.67	2.70	0.91	2.56
Cont. DTM	-1.98	-0.28	1.30	-0.37	3.02	3.04	0.90	2.53

DSM - digital landscape canopy surface model, DTM - digital terrain model (ground surface model)
* in metres

Morphometry of the DEMs was parameterised by two measures of surface roughness – area ratio and inverted vector strength (Fisher's K) defined in Grohman (2004). Both parameters were calculated for a 5x5 moving-window neighbourhood. It was hypothesized that the variation of residual values can be related to the local variation in slope angle and slope aspect, rather than directly to their values. Frequency and spatial distribution of aspect values depend on the section of landscape and its configuration, thus investigating relationships directly via aspect values would be biased or inconsistent. Also, conducting regression would be complicated due to circularity of aspect values. Area ratio roughness is the ratio of real surface area to the area of its orthogonal projection. Fisher's K defines the dispersion of unit vectors normal to the surface. While the first measure is sensitive to the local variation of the slope angle the latter is sensitive to the variation of the slope aspect. Very weak negative linear relationship was identified between the two roughness measures so that they were considered uncorrelated. The relationship between the DEM residuals and the corresponding DEM roughness was analysed with OLS and GWR. The GWR parameters were calculated for the grid nodes of the DEMs. The Gaussian kernel and bandwidth of 15 metres were used. All the data were analysed and visualized in R (R Development Core Team, 2008) and GRASS GIS (GRASS Development Team, 2008). Details on the calculation of Moran's I and GWR can be found in Bivand et al. (2008). The summary statistics of OLS and GWR coefficient of determination (R^2) are found in Tab. 2.

Tab. 2 Summary statistics of R2 for OLS and GWR of the DEM residuals and corresponding roughness of the DEMs.

DEM residuals against DEM roughness	OLS R^2	GWR R^2 *1st Qrt*	GWR R^2 *Median*	GWR R^2 *3rd Qrt*
InSAR DSM vs AR	0.024	0.273	0.497	0.676
InSAR DTM vs AR	0.03	0.185	0.402	0.642
Photog.DTM vs AR	0.016	0.235	0.466	0.692
Cont. DTM vs AR	0.014	0.234	0.466	0.711
InSAR DSM vs K	0.023	0.202	0.456	0.668
InSAR DTM vs K	0.016	0.184	0.405	0.638
Photog.DTM vs K	0.001	0.201	0.427	0.665
Cont. DTM vs K	0.017	0.187	0.419	0.683

AR - area ratio, K - Fisher's K roughness

4. Results

The summary statistics of DEM residuals presented in Tab. 1 provide an approximate picture of their distribution. The RMSEs are much higher than the stated accuracy which can be attributed to the considerable variation of terrain. In terms of spatial structure, Moran's I indicated significant spatial clustering of the DEM. Random spatial variation of residuals was more dominant in areas where no trend in elevation was present, such as the flat valley floor. However, the residuals were more spatially autocorrelated on slopes, generally across areas with a large scale trend present in the DEM. D'Agositno tests showed the residuals for each DEM were not normally distributed. Normal probability plots suggested normal distribution within the high frequency domain but the more extreme residual values deviate (tails of distribution of the residuals).

The spatial pattern of the DEM surface was apparent and any artefacts clearly visible in the roughness maps. InSAR DSM and less so the LiDAR DEM_{REF} exhibit very high degree of roughness which explains the patterns of slope angle and profile curvature. The inclined part of the area appears as rough and can be clearly distinguished from flat valley floor. As the area ratio map was based on slope angle, the effect of the larger-scale trends in the elevation data causes a bias in the area ratio due to the overall inclination within the moving window. The area ratio roughness distinguished the InSAR DTM, Photog. DTM, Cont. DTM as smooth surfaces while InSAR DSM manifested as the roughest surface especially within the valley floor even though the region is flat and relatively smooth on the LiDAR DEM_{REF} (Fig. 1).

The DEMs were more distinct in terms of the surface roughness if measured as Fisher's K than area ratio. This clearly identified the InSAR DSM as very rough due to the random short-range noise which was markedly filtered out in the InSAR DTM. Also the regions appearing as rough on area ratio maps were smooth in the Fisher's K maps. These are artificially smoothed west facing slopes of deep gorges and narrow ridges identifiable in the InSAR DEMs and LiDAR DEM_{REF}. The findings of the OLS regression reported in Tab. 2 show no apparent linear relationship between surface roughness and the DEM residuals. However, locally the relationship is evident and geographically weighted approach increases the R2 on average (Fig. 1 D).

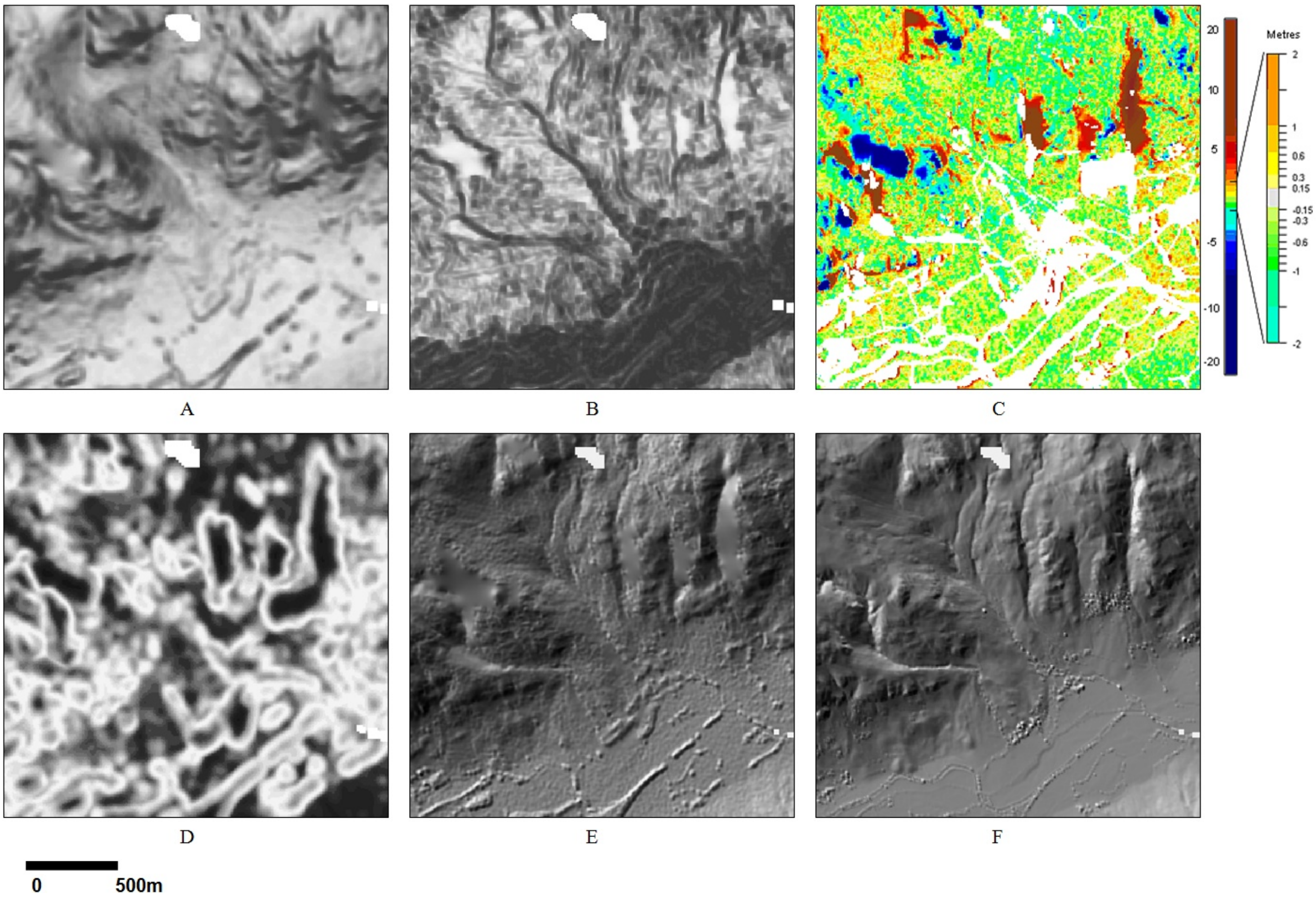

Figure 1. Examples of the analyses map outputs. A – InSAR DSM area ratio roughness, B – InSAR DSM Fisher's K roughness, (the roughness increases from white to black tones), C – InSAR DSM elevation residuals with masked above-ground surface objects (R2 increase from white to black tones), D – R2 of the GWR between InSAR DSM residuals and InSAR DSM area ratio roughness, E - InSAR shaded relief, and F – LiDAR DEMREF shaded relief.

5. Conclusions

The results show that globally no linear relationship exists between the surface roughness and DEM residuals but it can be very diverse locally. High elevation error occurs along DEM artefacts and sharply defined landforms which can be easily identified by area ratio and inverted vector strength surface roughness. Local approach with GWR provided evidence of locally existing relationship with surface roughness. The relationship between DEM errors and DEM roughness is diverse on local level. Problematic locations of DEMs were related to DEM artefacts and rough topography. The approach applied in the paper is useful for their identification and further treatment. The research also shows that the assumption of stationarity and Gaussian distribution of the DEM error field is questionable, but further research is needed to explore the spatial relationship between residuals and surface morphometry or land cover. Future work should focus on validation of traditional approaches of DEM error modelling. For example, conditional stochastic simulation as presented in Hunter and Goodchild (1997) or Wechsler and Kroll (2006) could be carried out with respect to the calculated DEM residuals distribution parameters under the assumption that the residuals provide the true picture of DEM error distribution and its complete coverage.

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