Geomorphometry and DEM Error

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Abstract—**Studies of DEM error have consistently found a link between terrain characteristics such as slope shape or steepness and error. This link is explored by looking at error in relation to various geomorphometric measures for a study area in Scotland. The magnitude of error is found to vary systematically between convex, planar and convex areas and measures of terrain roughness show some degree of correlation with error. These results suggest that it may be possible to produce better models of DEM error which are based on the nature of the terrain instead of the usual assumption that DEM error has the same characteristics across the DEM.**

INTRODUCTION

There is a growing body of literature on the subject of errors in Digital Terrain Models [2] which can be broadly split into two areas. First there is the study of the nature and causes of error itself and secondly the study of how these errors propagate through into the analytical use of the DEM. It is unsurprising that the nature of the terrain which is being measured and modelled has an influence in both. The purpose of this paper is to present a brief overview of the link between terrain characteristics and DEM error and then to present some results which illustrate the potential of geomorphometry in the modeling of DEM Error

A distinction can be made between errors in the height values in a DEM and errors which arise when the DEM is used for analysis. In some cases the analysis makes direct use of the elevation values and so the two are the same. However the majority of DEM analysis use the elevation values to derive other measures or outputs and so the propagation of errors becomes an issue. Here a further distinction can be made between measures which are based on the elevation values immediately neighbouring a point, such as gradient, aspect and flow direction , and those in which the results depend on values from a wider area such as flow accumulation, watersheds and viewsheds. For the first category it is possible to derive analytical results for error propagation by making assumptions about the nature of the initial elevation error [3], [11] and indeed some authors [3] argue that this is the best approach. However empirical studies still have a value and these have repeatedly shown that there is a link between the nature of the error in slope derivatives and the nature of the terrain. For the second category an analytical approach would be much more difficult and so studies have all been empirical in nature.

To date the majority of studies have focused on bare-earth DTMs often derived from field measurements or maps. The effect of topography on DSMs derived from Remote Sensing is likely to be somewhat different. For instance in the case of LiDAR, it was found [6] that it is the nature of the surface cover which is important rather than the nature of the topographic surface. Because of this the current paper will only consider bare earth DEMs

One common approach is to compare results from areas of upland and lowland topography [4] but some have examined the relationship between specific topographic measures such as gradient and surface roughness and error [1]. For instance in the case of elevation and slope gradient it has generally been found that errors are greater in upland areas and on steeper slopes.

It is suggested here that the nature of the terrain could play an even more central role in understanding DEM error. A long standing requirement is to be able to understand and model the spatial pattern of DEM error. One area where this is key is in Monte Carlo simulation of error propagation in which the error is usually modelled by as a spatially autocorrelated Gaussian field [5]. This assumes that error has the same characteristics everywhere even though it is well known that this is not the case. However if the link between the geomorphometry of a landscape and DEM error can be better understood then this opens up the possibility of more realistic models of DEM error which vary spatially and are based on the nature of the terrain surface itself

DTM ERROR AND TERRAIN SHAPE

The work makes use of a technique for producing a large sample of interpolation error values in which an existing DTM is resampled to a lower resolution and then re-interpolated back to the original resolution [9]. At the points which were dropped in the resampling process there is an estimate of interpolation error and since there is a large number of these, evenly distributed across the DTM, this allows a detailed analysis of the link between terrain characteristics and DTM error [9]. The method was applied to a portion of the British Ordnance Survey 50m PANORAMA DEM for a 50km squared area in Scotland which contained topographies ranging from mountains to a flat coastal plain. The DEM was resampled to data spacings ranging from 100m to 1600m and two different interpolation methods used to re-interpolate back to 50m: Inverse Distance Weighting (ID) and a Radial Basis Function Spline (RS). The methods were deliberately selected to represent interpolation methods which were thought to represent the range from poor (ID) to good (RS)

The results from earlier work [8] suggested that error might have different characteristics in convex, concave and planar parts of the landscape. In order to test this, Landserf [10] was used to classify the terrain according to its shape. Landserf works by fitting a polynomial surface to the elevations within a window around a point in a Digital Elevation Model (DEM) and then classifying the points based on the shape of this surface. For instance if the surface is concave in all directions then the point is the lowest point within the window and is classified as a pit. Valleys are pixels in which the surface is concave in direction (across the valley) and planar in the perpendicular direction (down the valley) and in all Landserf has six classes as shown in Table I

The size of the window can be varied and this affects the scale over which the landscape is classified. With a window size of 21x21 (Fig 1) the effective spatial scale of the features is 1000m, the distance between the outermost data points. The classification was also run at scales of 100m, 500m, 1500m and 2500m

TABLE I. LANDSERF CLASSES

Number	Landform class	Colour
1	Pit	Black
2	Channel	Blue
3	Pass	Green
4	Ridge	Yellow
5	Peak	Red
6	Plane	Grey

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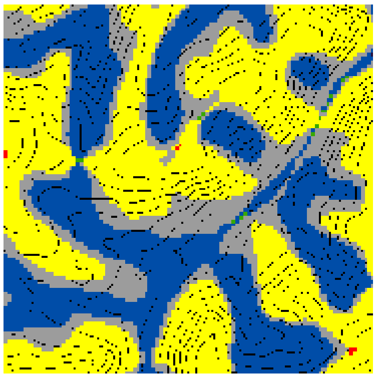

Figure 1. Landserf classification at three of the window sizes used.– the colours are as listed in Table 1

The DEM error points were then classified according to which landform they fell in and then ANOVA was used to test whether there was a systematic difference between the error values for each class. To see how the results varied with the scale of the landscape classification this analysis was carried out on a DEM produced by Bilinear Interpolation data points 800m apart (Table II). The results show that the degree of separation is very strong indeed. The tests all have p values which are less than 0.0001. The greatest separation is when the landscape is classified at a scale of 1000m, which as Fig. 1 shows is when the classification distinguishes the major valleys and ridges in this particular landscape. Figure 2 shows the means and 95% confidence intervals for this case and as can be seen there is clear separation between all 6 classes. The mean error values are negative for the convex landform classes (peaks and ridges, positive for the concave ones (pits and valleys) and close to zero for planar slopes and passes.

TABLE II. **ANOVA F STATISTICS FOR DIFFERENT WINDOW SIZES IN LANDSERF**

	Window size (m)				
	100	500	1000	1500	2500
F statistic	17381	61630	65214	42214	13472

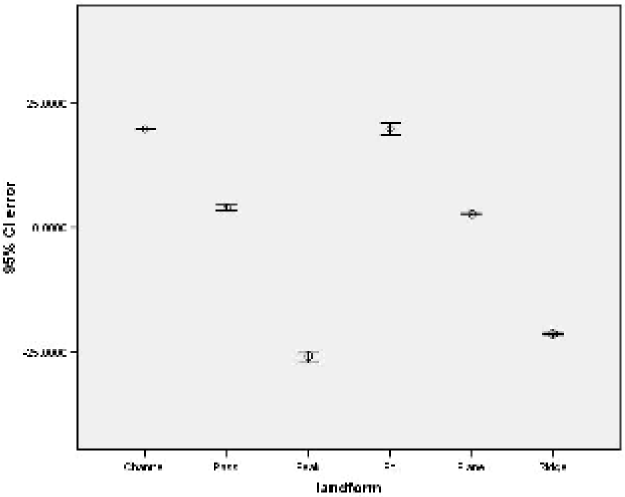

Figure 2. Means and 95% confidence intervals of elevation error by landserf class

The analysis was then repeated for DEMs produced by both methods from data points resampled to spacings ranging from 100m to 1600m, using the landserf classes produced at a scale of 1000m. The results of the ANOVA tests (Table III) indicate that the degree of separation between the landform classes, as expressed by the F statistic, tends to increase as the density of the original data points falls. This seems intuitively reasonable since as the data density falls, the ability of the interpolated surface to capture the shape of the true surface will diminish and in a way which will depend on just how concave or concave the real surface is. It is also interesting to note that the spline method clearly does a better job of modelling the shape of the surface in the case of data spacings below 800m. The F values are still statistically significant, but they are much smaller than for ID.

The area was subdivided into 256 contiguous 3km x 3km zones, and the analysis repeated separately for each, to see whether the degree of separation of error between landform classes varied systematically by terrain type. The F values varied between 12.5 and 2471 but the values did not appear to show any systematic pattern spatially and there was no correlation between the F value and measures of terrain roughness such as mean slope and standard deviation of slope.

TABLE III. **ANOVA F STATISTICS FOR DEMS CREATED FROM DATA OF VARYING DENSITY**

Interpolation	**Spacing of source data points (m)**				
	100	**200**	**400**	**800**	**1600**
ID	13962	33474	64388	65844	48220
RS	213	538	2138	28138	43125

DEM ERROR AND TERRAIN ROUGHNESS

A measure which extends the analysis beyond simply a classification into convex and concave is the Difference from Mean Elevation (DFME) which is the difference between elevation at a point and mean elevation within a defined distance around that point [7]. Positive values indicate a point which is higher than the local area and negative a point which is lower. This can also be thought of as a simple measure of the roughness of the terrain, for which the more commonly used measure is the standard deviation of slope (STDslope).

For both these measures a decision has to be made about the size of the window to use in their caclulation. The measures were calculated using a range of window sizes, as shown in Table IV and then the values correlated with elevation error for each DEM point. The results for DFME correspond very closely with those from Landserf in that the maximum value of the correlation coefficient occur when the terrain measure is calculated over a scale of about 1km. For STDslope the window size makes little difference and so a window of 1000m was used for comparability with the other measures.

The results (Table V) show that for both measures the link between roughness and DEM error becomes stronger as the density of the data points used in the DEM creation falls. Similarly the influence of terrain shape is strongest with the linear interpolation methods (ID) and less strong with the spline method. In fact when the spacing of the input data points is 400m or below for the spline method there is no correlation at all. Of the two measures DFME appears to have a stronger correlation with error which is possibly surprising since STDslope seems to be a more comprehensive measure of surface roughness. Finally, as with Landserf, repeating the analysis for the 256 sub-areas showed no link between the strength of the relationship and terrain roughness.

TABLE IV. **PEARSON COEFFICIENT OF VARIATION FOR RELATIONSHIP BETWEEN TERRAIN MEASURES AND ELEVATION ERROR AT VARYING WINDOW SIZES**

Terrain Measure	**Window size (m)**				
	100	**500**	**1000**	**1500**	**2500**
DFME	0.00	0.53	0.71	0.72	0.61
STDslope	0.27	0.37	0.34	0.31	0.28

TABLE V. PEARSON COEFFICIENT OF VARIATION FOR RELATIONSHIP BETWEEN TERRAIN MEASURES AND ELEVATION ERROR

Terrain measure	Interpolation	Spacing of source data points (m)				
		100	**200**	**400**	**800**	**1600**
DFME	ID	0.58	0.86	0.89	0.65	0.68
	RS	0.01	0.01	0.20	0.44	0.41
Roughness	ID	0.22	0.30	0.35	0.36	0.33
	RS	0.11	0.17	0.23	0.26	0.30

CONCLUSION

These initial experiments suggest that it may be possible to to improve the models of DEM error used in the analysis of error propagation by moving away from a single measure applied across the whole DEM to one which varies according to the underlying terrain. A simple classification into convex, concave and planar areas showed that elevation errors were systematically different between the three areas.

DFME shows some promise as a per-pixel measure which correlates well with error in some cases which might allow elevation error to be modelled for each pixel. However DFME is less good when data density is high, especially with DEMs created using spline interpolation and other measure of terrain characteristics need to be explored as alternatives. Interestingly the more commonly used STDslope measure correlated quite poorly with error in most cases.

Further work is needed to see whether these results can be replicated in other terrain types and to see whether the link between the geomorphometric measures and DEM error can be calibrated to produce useful estimates of DEM error.

ACKNOWLEDGMENT

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