The Accuracy of Gridded Digital Elevation Models Interpolated to Higher Resolution

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1. Introduction

The issue of the accuracy of Digital Elevation Models has received a good deal of attention in recent years as made clear by the review of Fisher and Tate (2006). The present work was motivated by the need to interpolate a coarse resolution global DEM to a finer resolution for the purposes of climatic modelling of the Greenland ice sheet (Hanna et al 2007). The question of how best to interpolate an exisiting DEM to a higher resolution has received only limited attention (Rees 2000, Kidner 2003) but the issue is one of general interest because

- It is commonly required in global modelling where some of the input datasets may only be available at relatively coarse scales.
- When interpolating from point or line data sources the spatial resolution of the input data is commonly less than that of the final DEM. For example, the British Ordnance Survey produce a 10m DEM from contours at 5m vertical interval. In areas where the slope of the land is less than 14 degrees, the contours are at least 20m apart i.e. twice the DEM resolution.

Both Rees (2000) and Kidner (2003) used the same methodology to explore this issue. An initial DEM is resampled to produce a grid of points at a lower resolution. These points are then used as the input to produce a DEM at the original resolution. For the points which are dropped in the resampling, a comprison of the original value and the interpolated value gives an estimate of interpolation error at that point. These can be used to estimate the Root Mean Square Error of elevatoin ($RMSE_{elev}$), the standard measure of DEM error.

$$RMSE_{elev} = \sqrt{\frac{\sum \left(z_p - z_o\right)^2}{n}} \qquad (1)$$

where Z_p = predicted elevation
Z_o = observed elevation

However, since there are a large number of such points, and they are distributed in space, this opens up the possibility of exploring a number of general issues relating to interpolation error and to the use of $RMSE_{elev}$ as a measure of error. This paper presents the results of some of the early work on this. Three questions are addressed briefly

1. Rees (2000) suggested that there was little benefit in using non-linear interpolation for interpolating to higher resolutions but Kidner (2003) demonstrated that non-linear methods produced lower RSMEelev values. However both authors only considered the case of doubling the DEM resolution, and only considered RMSEelev – here consideration is given to a wider range of resampliigs and to other measures of

quality.

2. $RMSE_{elev}$ has been criticised as a measure of error on a number of grounds (Wise 1998, 2000). One of these is that since small errors in elevation may lead to large errors in surface derivatives such as slope and aspect it may be a poor predictor of these errors. This question is explored here.
3. Since the number of points from which to estimate RMSE directly is usually small it is not possible to consider the spatial pattern of error or the possible link between error and the nature of the terrain surface, such as terrain roughness. Some initial observations on both these points are made here.

2. Study Area and Methodology

In order to consider the possible effect of terrain roughness an area was selected in the Cairngorm Mountains of Scotland (Figure 1) which covered both the rugged mountain terrain and the low lying areas near the coast. A subset of the Ordnance Survey PANORAMA 50m DEM was selected with 1024 points in both X and Y. This number of points allows reduction of the resolution in both X andY by factors of 2,4,8,16 and 32. In all cases the initial corner points are retained as data points after resampling so that interpolation back to the original resolution never involves extrapolation outside the area of the input data points.

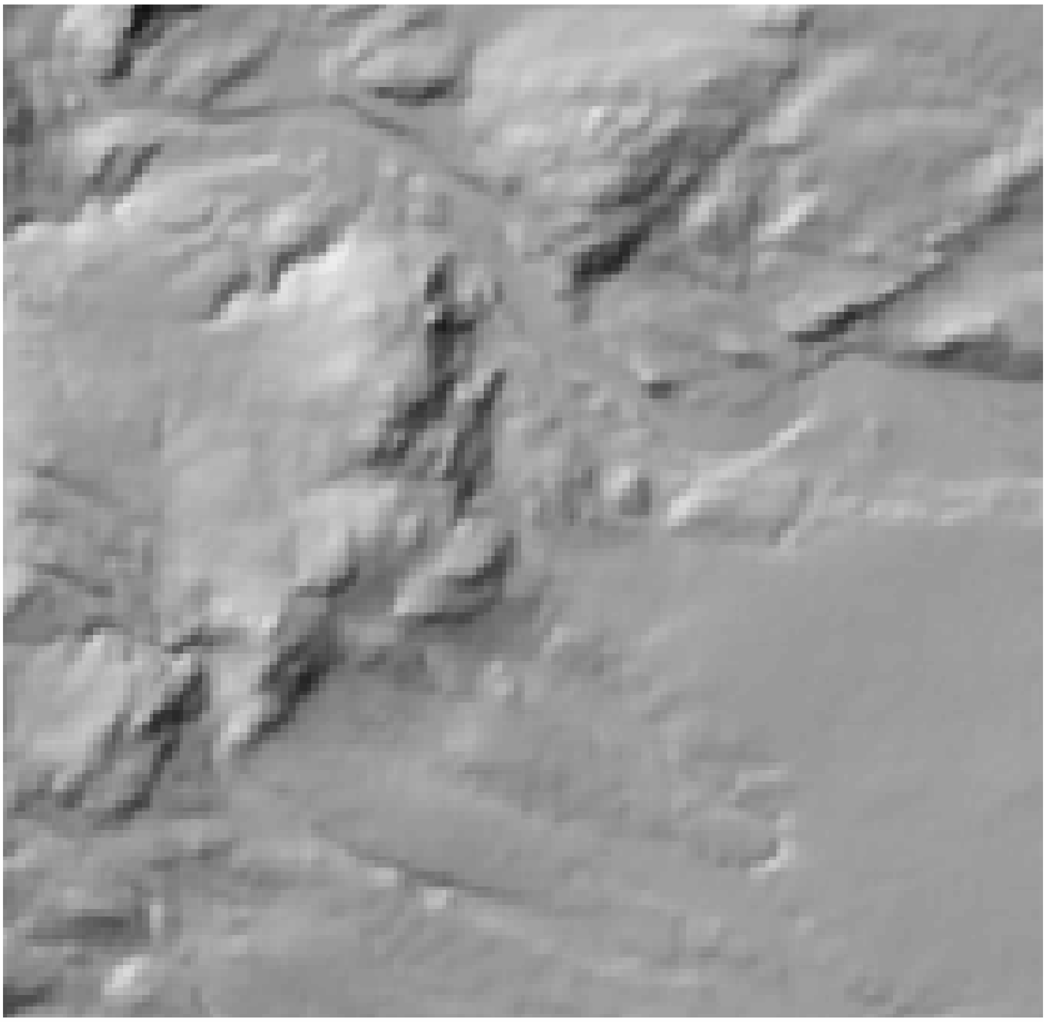

Figure 1. Study area in the Cairngorms of Scotland. The lower left corner of the area has OS coordinates 300000,735000 and the DTM has 1025x1025 pixels at 50m resolution.

Six commonly-used interpolation methods were used in the study – the two letter abbreviations are used in the presentation of some of the results

1. Bilinear interpolation (BL)
2. Inverse Distance Weighting (ID)
3. Radial Basis Function. The Spline option was selected after some initial trials (RS)
4. Spline (SP)
5. Local Polynomial (LP)
6. Topo to Raster. This implements Hutchinson's ANUDEM method and in ARC/INFO was called TopoGrid (TG)

The first four are exact interpolators, which honour the original data points. The last two are approximate interpolators which do not guarantee to honour the original data points. The first method was implemented using a purpose written program – the others were run from ArcGIS 9.2.

3. Results

Table 1 presents summary statistics on RMSEelev for all six methods and the full range of resamplings. For simplicity RMSE is calculated for all data points, including those which were retained after resampling, where for exact interpolators the error will be zero by definition. As Table 1 shows, restricting the caclulations to those points which were not input points has a negligible effect on the results.

		BL	ID	LP	RS	SP	TG
Type		Exact	Exact	Approx	Exact	Exact	Approx
32	rmse	51.09	54.16	52.20	52.85	51.94	
	rmse-nd	51.12	54.19	52.23	52.88	51.97	
	mean	0.67	0.65	0.62	0.78	0.74	
	max	342.56	325.96	326.62	377.36	375.65	
16	rmse	28.21	33.21	28.43	26.96	26.61	
	rmse-nd	28.27	33.28	28.49	27.02	26.67	
	mean	-0.25	-0.24	-0.25	-0.31	-0.36	
	max	225.60	244.37	222.45	276.45	259.50	
8	rmse	12.81	17.56	13.10	10.42	10.35	15.17
	rmse-nd	12.92	17.70	13.21	10.50	10.44	15.28
	mean	0.02	0.02	0.02	0.01	0.01	-2.28
	max	135.56	147.84	133.40	164.21	158.14	350.89
4	rmse	5.06	7.89	5.25	3.82	3.77	7.24
	rmse-nd	5.23	8.15	5.43	3.95	3.89	7.37
	mean	-0.01	-0.02	-0.01	-0.01	-0.01	-0.75
	max	82.62	105.52	84.19	69.16	67.42	223.36
2	rmse	1.96	3.11	2.09	1.58	1.59	5.29
	rmse-nd	2.27	3.60	2.41	1.83	1.83	5.38
	mean	0.0	0.0	-0.01	0.0	0.0	-0.41
	max	55.0	67.53	57.51	51.86	50.37	362.19

Table 1. Elevation error statistics for different interpolation methods at different levels of resampling. The values are as follows: rmse – rmse for all points; rmse-nd – rmse for points

not falling on an original data point; mean – mean error; max – maximum value of absolute error. Note: The TOPOGRID algorithm failed to process the 16 and 32-fold resampled sets.

The results do not support the suggestion that non-linear methods always perform better than simple bilinear interpolation in terms of $RMSE_{elev}$. At low levels of resampling two of the spline-based methods (RS and SP) perform best while the third (TG) performs worst. Simple bilinear interpolation consistently produces lower RMSE values than IDW. As the resampling level increases (i.e. as the number of input data points decreases) the difference between the methods reduces.

However visual inspection of hillshade images for the different DEMs shows marked differences between the results (Figure 2). Bilinear interpolation produces very strong linear artefacts, which become more pronounced as the resampling level increases. Spline-based methods on the other hand produce smooth DEMs even when resampling has greatly reduced the number of input data points.

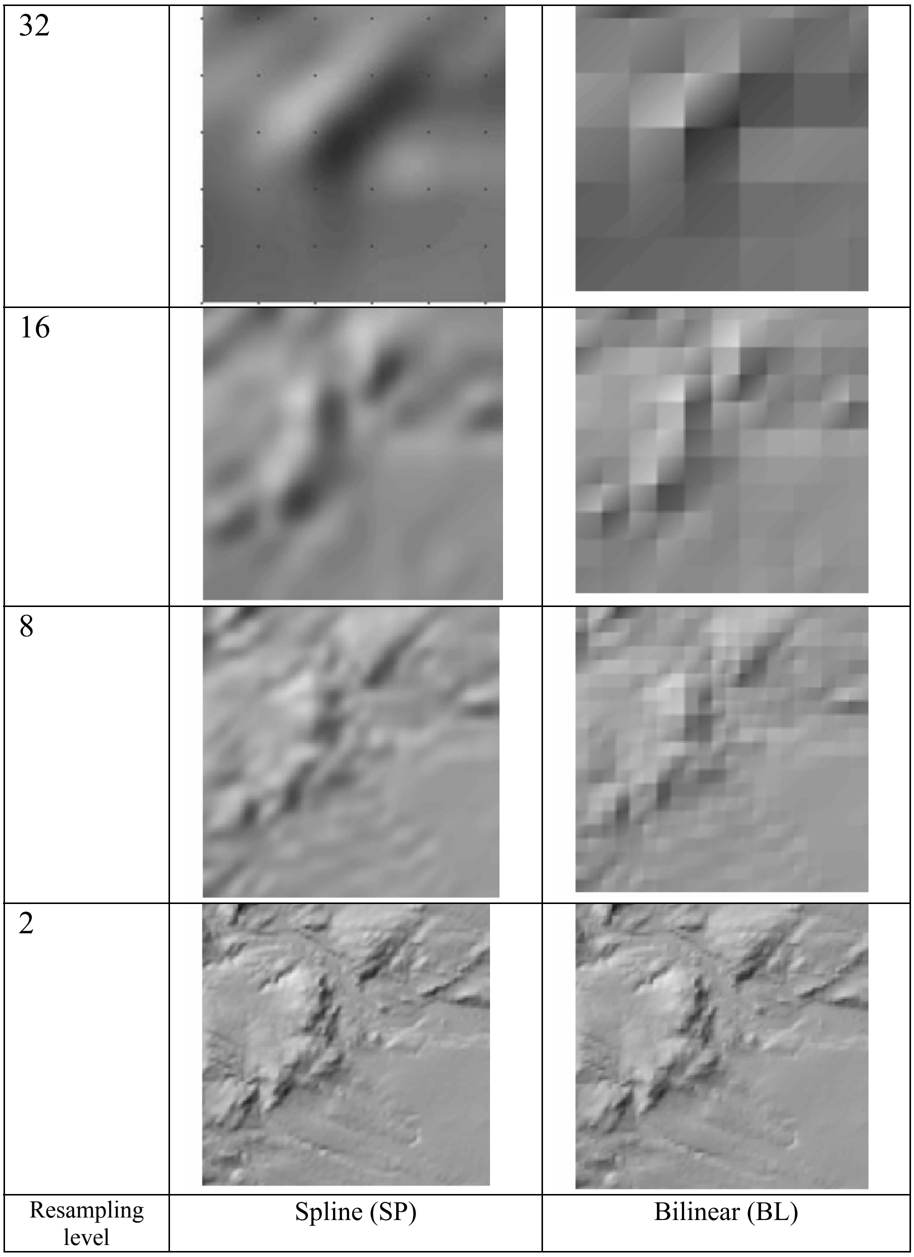

Figure 2. Hillshade images for 2 of the interpolation methods, for selected resampling levels.

By estimating RMSE of elevation and of gradient and aspect for all DEMs (ie. all methods at all resampling levels) it was possible to see how well RMSEelev predicts overall error levels in derived surface values. As Table 2 shows, the relationship is very strong in the case of gradient and aspect but very weak in the case of curvature. This suggests that , despite its shortcoming, $RMSE_{elev}$ may in fact be a reasonable predictor of error in some derived characateristics.

Terrain characteristic	R^2	Best fit line (x = RMSE Elevation)
Gradient	0.974	y = 1.9869Ln(x) - 0.5333
Aspect	0.960	y = 17.418Ln(x) + 3.7808
Curvature	0.211	y = 0.0147Ln(x) + 0.2447

Table 2 Relationship between RMSE of elevation and RMSE of selected terrain characteristics.

There has been a good deal of interest in the spatial characteristics of DEM error (Fisher 1998, Hunter and Goodchild 1997) with numerous authors proposing models of DEM error based on spatial autocorrrelation. Table 3 shows the results of calculating Moran's I on the error values in all DEMs. At low levels of resampling (i.e. when input data volumes are high) the values vary greatly between methods and are often rather low, suggesting that a global autocorrelation function may be a poor model of DEM error in these cases. As the resampling level increases, autocorrelation in the error increases, which is to be expected as most pixels in the final DEM are being interpolated from the same input points as are their neighbours.

	BL	ID	LP	RS	SP	TG
32	.98	.98	.98	.98	.98	
16	.97	.98	.97	.97	.97	
8	.93	.95	.93	.91	.92	.94
4	.78	.84	.80	.72	.73	.88
2	.40	.66	.48	.35	.35	.84

Table 3: Spatial autocorrelation of error in elevation measured using Moran's I.

The results show a consistent relationship between terrain roughness and error, with higher error values in the more rugged upland areas (Figure 2). Table 4 shows the correlation coefficients between Standard Deviation of Slope (a measure of terrain roughness) and RMSEelev. When roughness is calculated from the original, full-resolution DEM (i.e. the results labelled STD1) it can be seen that it is a good predictor of error, even at high resampling levels. In most applications of course, the only data available will be the lower resolution data. When this is used to calculate roughness the results are still quite good at low levels of resampling, but fall away as the resolution of the input data becomes too coarse to estimate roughness reliably.

		BL	ID	LP	RS	SP	TG
32	STD1	0.63	0.53	0.62	0.63	0.64	
	STD32	0.22	0.11	0.26	0.51	0.41	
16	STD1	0.78	0.70	0.78	0.73	0.72	
	STD16	0.58	0.55	0.58	0.39	0.47	
8	STD1	0.91	0.85	0.91	0.85	0.86	0.87
	STD8	0.76	0.81	0.78	0.58	0.58	0.73
4	STD1	0.93	0.95	0.94	0.85	0.85	0.87
	STD4	0.87	0.90	0.88	0.80	0.79	0.75
2	STD1	0.90	0.94	0.91	0.86	0.87	0.78
	STD2	0.89	0.92	0.89	0.87	0.87	0.75

Table 4. Correlation between RMSEelev and terrain roughness. STD1 is the Standard deviation of slope measured from the original DEM (i.e. at a resampling of 1). STD32 etc is the STDslope measured from the DEM interpolated from the data resampled at level 32 etc

4. Conclusions

This paper has presented a summary of some of the findings of a study of DEM error. The main conclusions which may be drawn are

1. From the evidence presented here, spline-based methods produce DEMs which have low RMSE values and also have a smooth appearance.
2. Depsite its acknowledged limitations. $RMSE_{elev}$ may in fact be a reasonable predictor of error in some surface derivatives.
3. The spatial pattern of DEM error may not always be modelled by a simple spatial autocorrelation function and models of DEM error should possibly consider how error is related to the characteristics of the terrain itself.

5. Acknowledgements

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Biography

Stephen Wise is a Senior Lecturer in GIS and author of a successful textbook 'GIS Basics'. His main research interests are the analysis of error propagation in DEMs and geomorphometry. He is a member of the GISRUK National Steering Committee (and was chairman and organiser of GISRUK 2002 in Sheffield) and is an Associate Editor of Computers and Geosciences.

Ed Hanna is a Senior Lecturer in Climate Change. His main research interests are in the link between climate change and the mass balance of ice-sheets. He is a Fellow of both the Royal Meteorological and Royal Astronomical Societies, has served as a Council member of the British Astronomical Association, and is an Editorial Board member of WEATHER (RMetS).

Tristram Irvine-Fynn is a PhD student working on water storage and the hydrological evolution of polythermal glaciers.