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Creating DEMs from Survey Data: Interpolation Methods and Determination of Accuracy

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ABSTRACT: Digital Elevation Models (DEMs) are becoming increasingly used in modern geomorphological studies. DEMs offer a number of benefits for the characterisation and monitoring of landforms. This paper aims to assess the impacts of interpolation approaches for generation of DEMs. The interpolation approach used for the raw survey data and any subsequent spatial analysis can be affected by errors in the DEMs, leading to potentially inaccurate conclusions being drawn. These errors can either be from the source data or as a consequence of the analysis procedure. Quantification and description of any potential error present for the interpolated datasets is carried out by Root Mean Square Error (RMSE). This is supplemented by analysis into the spatial structure and distribution of the datasets via summary statistics and Q-Q plots. Several of the most common interpolation approaches for the generation of survey data are reviewed here. A case study of applying multiple interpolation approaches to a Terrestrial LiDAR Scan (TLS) dataset is presented. This demonstrates the effect the interpolation approach has on the spatial structure and derivatives of DEMs. Whilst DEMs are used in many geomorphological studies there has to be a tailored, 'site-specific' interpolation approach based on study area, data source, terrain morphology and characteristics.

KEYWORDS: Digital Elevation Models, interpolation approaches, error statistics, terrain derivatives, spatial analysis

Introduction

The use of Digital Elevation Models (DEMs) in the analysis and characterisation of the landscape is beneficial in modern geomorphological studies. DEM spatial analysis not only provides a description of the landscape, but is the foundation of three-dimensional analysis from which other morphological descriptors can be derived (Zhou and Liu, 2004). These descriptors include slope, aspect, curvature (Pirotti and Tarolli, 2010) and roughness (McKean and Roering, 2004; Pollyea and Fariley, 2011). Interpolation of survey data for the creation of DEMs is becoming increasingly frequent in geomorphology (Prokop and Panholzer, 2009; Rayburg, 2009; Aguilar et al. 2010). DEMs are used in studies ranging from landslide analysis (McKean and Roering, 2004; Scheidl et al. 2008), rockfall analysis (Nguyen et al., 2011) fluvial geomorphology (Heritage and Hetherington, 2007) and landscape characterisation (Glenn et al., 2006). The recent development of progressively higher resolution datasets such as aerial Light Detection and Ranging (LiDAR) systems and Terrestrial LiDAR Systems (TLS) results in the interpolation approaches to the raw data often being overlooked (Brunsdon, 2009). Increased data resolution results in demand for answering questions about data at finer resolutions.

Assessing the causes and propagation of error in DEMs is useful when dealing with large amounts of data (Fisher and Tate, 2006). The propagation of DEM error and the impact on terrain derivatives including slope and aspect is an issue when generating DEMs from survey data (Hunter and Goodchild, 2007). Errors in the base DEM or from the interpolation approach will have a detrimental effect on the terrain derivatives (Kienzle, 2004; Aguilar et al., 2005). Small errors in the generation of the DEM can lead to inaccurate slope, aspect and curvature derivatives which in turn will lead to inaccurate predictions and conclusions (Januchowski et al., 2010). The interpolation approach used for spatial data analysis can influence the accuracy / quality of the surface produced (Lloyd and Atkinson, 2001; Heritage et al., 2009).

There is often little thought given to the implication that the choice of interpolation approach will have on the generation of the points to a regular DEM grid. This aim of this paper is to assess the impact of interpolation approaches for the generation of DEMs from survey data. Objectives include the creation of DEMs from survey data using multiple interpolation approaches. Summarising and identifying sources of error arising from the interpolation approach is also assessed. The method presented enables the interpolated DEMs to be assessed in terms of the statistical characteristics of error, spatial statistical structure and deviance of distribution as a means to easily understand spatial structure. Providing an insight into the best available interpolation approach when creating DEMs for analysis.

Interpolation methods available for creating DEMs

Accurate interpolation of survey data, is essential for accurate conclusions and validations to be accomplished. Numerous interpolation approaches can be applied to produce DEMs from survey data (Podobnikar, 2005). Interpolation approaches for the purposes of this article will be limited to four readily available interpolation approaches for the generation of DEMs from survey data.

Inverse Distance Weighting (IDW) is an exact interpolator with the predicted values at locations being the same as the observed values (Lloyd 2007). IDW works on a local neighbourhood approach on the assumption that the value at any unsampled point is a weighted average of the values of points within a certain cutoff distance. The weights are inversely proportional to the power of the distance (Burrough and McDonnell,1998; Mitas and Mitasova, 2005). Advantages of IDW are the easy implementation of the technique within GIS programs and that interpolations using IDW are not computer RAM intensive to produce.

Radial Basis Functions (RBF) are a group of exact interpolators that use a basic equation dependent on the distance between the interpolated point and the sampling points (Aguilar et al., 2005). RBF utilises splines, hypothetical surfaces that are fitted to some local subset of the data. The analogy often used for splines within RBF is the imitation of a rubber membrane passing through all the data points. The key advantage of the splines interpolated using a RBF from survey data is the amount of control, which can be achieved in the smoothing or tension of the final surface. A spline can be forced to fit through data points or can be smoothed (Lloyd 2007). The advantage of controlling the splines fit to the data is that it is possible to make predictions outside the range of data, so peaks of values that are not necessarily sampled may still be predicted. In addition, smoothing of the spline, as oppose to forcing it through all of the datapoints, resulting in a smoothed surface. This is beneficial where potential local small-scale variation in surfaces can affect the outcome of the generated surface, producing a noisy output. Disadvantages of the RBF are the stiffness and tension of the membrane applied for generation can create large gradients. Processing time is also significantly longer than other approaches due to the number of points being sampled. Additionally, derivatives of the process might cause difficulties in morphological analysis (Mitas and Mitasova, 2005).

Two RBF interpolators are used in this method, Spline with Tension (SPT) and Thin Plate Spline (TPS). SPT differs from TPS due to the tensioning variable that is introduced in the algorithm, which can provide a better fit to the data. Advantages of the SPT include the smoothing parameter whereas TPS exhibits a more rigid interpolation approach from the generation of surfaces. TPS does not offer as much control in terms of fitting of the predicted surface to the datapoints (Lloyd, 2007). TPS advantages include the retention of small-scale features, which is in contrast to weighted averages and trend surfaces (Burrough and McDonnell, 1998).

Ordinary Kriging (OK) is one of the most widely used forms of prediction from geostatistical analysis, this allows the mean of the values, in this case elevation, to vary and is estimated for each prediction neighbourhood (Lloyd, 2007). The process of kriging can be simplified into; generation of a variogram, fitting a model to variogram, using a model in kriging and finalising the output of kriging. Kriging assumes that the spatial distribution of phenomena can be modeled using a random function. This random function for variation can be split into a deterministic component, representing change over the study area, and a stochastic, or random, component. The random function therefore reflects the uncertainty of spatial variables and parameters. Kriging develops the random function on the basis of the generation of a variogram, a measure of the spatial variability of a particular variable.

The variogram is used to assess the degree to which values differ according to how far apart they are in space (Lloyd, 2007). Lag of the variogram is used to describe distance by which observations are separated. Elements and measures of the variance are estimated by calculating the squared differences between paired observations separated by their lag. The variogram therefore characterizes the degree of difference in values as a function of the distance that they are separated by (Lloyd, 2007; pp. 142). A variogram can then be fitted with a mathematical model used as a tool to estimate how close a measured point is to an interpolated one.

The variogram model is used within kriging as a means of finding appropriate weights for available observations and using the model fitted to the variogram to obtain the predicted values. Kriging is computed using a weighted average assigning greater weights to closer locations, with these weights being computed from the variogram (Brunsdon, 2009). The generated predicted variables within the neighbourhood controlled by the variogram model are used for the interpolation and generation of surfaces (Goovaerts 2002; Lloyd and Atkinson 2002a; Lloyd and Atkinson 2002b; Lloyd and Atkinson 2006). Disadvantages of Kriging are it is a relatively complex process with numerous forms and numerous models that can be applied for the prediction of variables (Lloyd, 2007).

Method for interpolating DEMs and error assessment

Survey data can be recorded and interpreted from monitoring equipment that records a fixed point in space. The workflow for collection of any survey dataset will now be explained following this an example using a collected TLS dataset will be used to illustrate this method.

Generating DEMs from survey data

As described, many interpolation approaches exist for the generation of survey data. For the purpose of this article the four approaches outlined in the previous section will be used, these are popular methods used to generate DEMs from survey data and are readily available in most software packages.
Post processing of the raw data is required before interpolation approaches can be applied. Operator based post-processing involves the removal of any erroneous or non-ground point from the dataset. Operator based post processing is not necessary if data are supplied in post-processed format. Post processing software is dependant on the survey data collection method and the manufacturer of survey equipment. This could be from total station, GPS, Remote sensing or LiDAR. This method allows interchangeable software procedures in preparing data for analysis. In general a processed ASCII .txt files, in this example from Leica Cyclone 5.4 (Leica, 2006), are exported and a shapefile is generated within the ArcGIS software (ESRI, 2010).

This method implements the Geostatistical Analyst Extension of ArcGIS 10. Following post processing of the raw data the interpolation approaches are applied and multiple DEMs generated. During interpolation a different number of nearest neighbours (16, 32, 64) are tested to assess the affect this has on the spatial structure and error statistics of the generated DEMs. Cross validation and error summary statistics in the form of the Root Mean Square Error (RMSE) are recorded during this stage. Summary statistical analysis of interpolated surface, along with computation time, are recorded in ArcGIS. Q-Q plots of interpolated surfaces are also generated within the Open Source R Programming Environment (R Project, 2012). Q-Q plots are used as a method for assessing error of the spatial structure of interpolated surfaces. The analysis scheme is detailed in Figure 1 and will be explained in more details in the following sections.

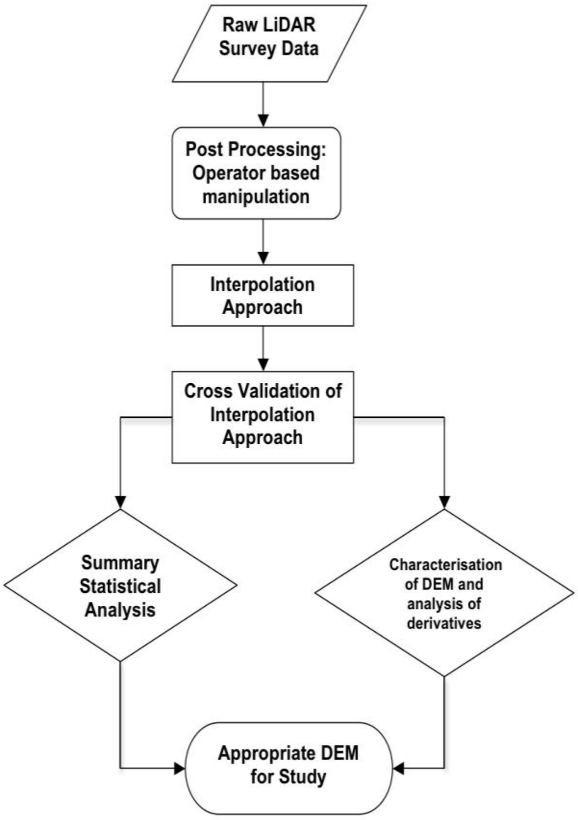

Figure 1: Analysis Scheme for assessment of interpolation approach

Error analysis of DEMs

One of the most common methods to measure DEM quality/accuracy is the Root Mean Square Error (RMSE) (Hunter and Goodchild, 1997; Fisher and Tate, 2006; Aquilar et al., 2005). The RMSE is given by the formula:

$$RMSE = \sqrt{\frac{\sum (z_{DEM} - z_{Ref})^2}{n}} \qquad (1)$$

Where Z_{DEM} = the measurement of elevation (or derivative) from DEM, Z_{REF} = higher accuracy measurement, from a sample *n*.
RMSE is a form of cross validation of the dataset, which involves removal of one observation using the remaining observations to predict the value of the removed value. This is then returned to the dataset and the next observed value is removed, and then repeated for the entire dataset (Lloyd, 2010). RMSE as validation measures the difference between observed versus predicted observations of the data providing a representation of the magnitude of error for a particular interpolation approach. The RMSE as a quality measure has a number of different formulas and can include the standard deviation of one surface against another (Keinzle, 2004: Fisher and Tate, 2006). Only formula (1) presented, is used in this example. The RMSE can be seen to give a quick and accurate assessment of the supposed DEM quality / accuracy from interpolation approaches, however, there are a number of drawbacks. RMSE is a global spatial measure, and therefore local spatial characteristics are not assessed. Statistical analysis and structure of the interpolated surfaces provide just as much information of the spatial structure and interpolation approach for the generation of DEMs from survey data (Wise, 2011).

Summary statistical analysis of generated surfaces

In addition to the RMSE, univariate statistics and Q-Q plots are used for an assessment of the interpolated surfaces. Univariate statistical analysis provides descriptive statistics for summarizing particular variables (Lloyd 2010). It includes statistical measures such as the minimum, maximum, standard deviation, skewness and kurtosis of the distribution of the interpolated surface. Univariate statistics have been used with reference to the assessment of interpolation methods by Heritage et al. (2007). One limitation of univariate statistics is that they obscure spatial variation within the study (Lloyd 2007). The ability for analysing distributions of error is based on the assumption that the distribution is normal and stationary. However, some studies suggest spatial autocorrelation statistics may be used for error from DEMs and survey data (Hunter and Goodchild, 1997; Gallay et al., 2010).

The Q-Q plot will be used to compare the structure of how the different interpolation approaches used to generate DEMs from survey data vary from each other in terms of application to the theoretical normal distribution. Therefore, providing an assessment of any sources of potential error when generating the DEMs. The diagnostic Q-Q plot should yield a straight line and any variance from the straight line of the interpolated surfaces suggests a strong deviation from the normal distribution, therefore error and potential erroneous results (Hohle and Hohle, 2009).

A highly variable output of difference between observed and theoretical quantiles within the interpolation approach, coupled with high variability from the histogram suggests that the interpolated surface may not be the best estimate for the characterisation and generation of DEMs. Analysis of the DEMs and derivatives is carried out on selected DEMs. These are selected depending on the error statistics, generally choosing a range of DEMs generated from different interpolation approaches for assessment. Finally, the most appropriate DEM for the study is selected.

Case study: Statistical analysis of interpolation approaches to LiDAR data

The dataset being used is a TLS survey of Minnis North, a mud-flowslide landform along the A2 Coastal Road, Northern Ireland (Figure 2). Failures due to saturation of the exposed Lias Clays on the hillslope results in periodic failures impacting on the road, blocking off local communities (Smith and Warke, 2001). TLS monitoring is being carried out to assess potential movement and morphological changes on the site. DEMs for each of the interpolation approaches were generated and univariate statistics recorded (Table 1).

Figure 2: Leica HDS3000 Scan station, Terrestrial LiDAR scanning surveying slope morphology, Co. Antrim, Northern Ireland.

The RMSE for TPS are consistently the highest of all the interpolation approaches followed by IDW and OK, with the lowest RMSE recorded for SPT (Table 1). The highest RMSE error also correlates with an overestimation and error in the minimum and maximum heights when generating the DEM. All interpolated surfaces illustrate negative skewness quite close to the mean suggesting the high resolution of the Terrestrial LiDAR dataset enables accurate interpolation of surfaces. TPS performs least favourably in terms of skewness with the distribution being more negatively skewed than other techniques. This is supported by the kurtosis of the distribution with TPS 16 neighbours showing the most peaked distribution around the mean. The standard deviation of the TPS is highest for all interpolation approaches demonstrating greatest variation in values around the mean. A greater spread of values and peak around mean suggests potential sources of error and a reduction in accuracy of the interpolation approach.

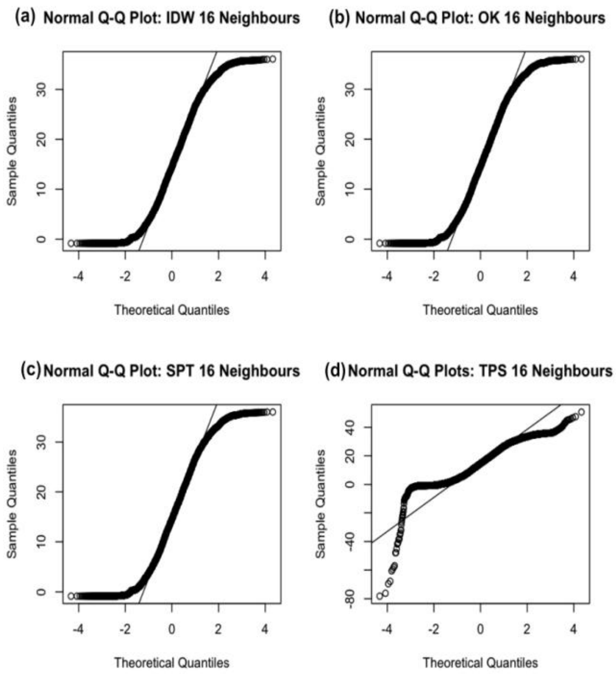

Figure 3: Probability Q-Q Plot of Interpolated Surfaces from LiDAR scan for (a) Inverse Distance Weighting 16 Neighbours (b) Ordinary Kriging 16 Neighbours (c)Spline with Tension with 16 Neighbours (d) Thin Plate Spline with 16 Neighbours

Table 1: Univariate statistical measure for multiple interpolation approaches for a single Terrestrial LiDAR Scan.

Interpolation Approaches; Inverse Distance Weighting (IDW), Ordinary Kriging (OK), Spline with Tension (SPT) and Thin Plate Splines (TPS). Summary statistics; Root Mean Square Error (RMSE), Mean Error (ME), Standard Deviation (St Dev), 1st Quartile (1st Q), 3rd Quartile (3rd Q), Interquartile Range (IQR), Skewness (Skew), Kurtosis (Kurt) and Processing Time (Time(s)).

		RMSE	ME	Mean	Min	Max	St Dev	1st Q	3rd Q	IQR	Skew	Kurt	Time (s)*
	16	0.181	0.0008	16.611	-0.859	36.111	9.835	8.218	24.903	16.685	-0.040	1.882	84
IDW	**32**	0.179	0.0009	16.614	-0.858	36.082	9.837	8.219	24.907	16.688	-0.040	1.881	95
	64	0.178	0.0011	16.618	-0.858	36.054	9.840	8.225	24.910	16.685	-0.040	1.880	136
	16	0.170	0.0002	16.670	-0.856	36.071	9.833	8.290	24.964	16.674	-0.043	1.882	187
OK	**32**	0.170	0.0002	16.672	-0.857	36.085	9.835	8.289	24.972	16.683	-0.043	1.881	382
	64	0.169	0.0003	16.611	-0.857	35.922	9.837	8.222	24.912	16.690	-0.041	1.879	1117
	16	0.163	0.0005	16.611	-0.859	36.020	9.835	8.221	24.902	16.681	-0.040	1.882	357
SPT	**32**	0.162	0.0004	16.612	-0.858	36.012	9.836	8.218	24.910	16.692	-0.041	1.881	789
	64	0.162	0.0001	16.613	-0.857	35.950	9.836	8.221	24.914	16.694	-0.041	1.880	2540
	16	0.866	0.0002	16.670	-139.30	75.663	9.938	8.333	24.957	16.624	-0.173	3.259	257
TPS	**32**	0.293	0.0002	16.665	-75.327	60.813	9.862	8.318	24.934	16.616	-0.066	2.081	457
	64	0.293	0.0002	16.664	-59.825	57.550	9.824	8.317	24.928	16.612	-0.052	1.969	1184

**Processing time on Macbook Pro, 2.4 GHz Intel Core 2 Duo, 8GB RAM running Bootcamp Partition, Windows 64 bit*

The probability Q-Q plots illustrated in Figure 3 for a sample of the interpolated surfaces, illustrate the non-normality of the interpolated surfaces. The TPS shows distinct non-normality with the residuals and outliers causing the plot to become skewed. The other interpolation approaches show similar plots with the tails of the distributions reflecting the summary univariate statistics.

Effect of Interpolation Approach on DEM and Derivatives

The effect of the interpolation approach on the generation of the DEM for this case study is highlighted in Figure 4. DEMs with the highest RMSE and most varying univariate statistics were used to illustrate the changes. Therefore DEMs with 16 neighbours were used in the analysis (Table 1). The DEMS are shown along with a derivative of the DEM, in this case slope.

Figure 4 indicates the interpolated DEMs using IDW, OK and SPT show little variation in their structure and the terrain derivative of slope. This supports the initial univariate statistical analysis. Most notably is that the TPS derived DEM illustrates large error and artefacts in both the DEM and subsequent terrain descriptor. This is shown by the predominance of lighter areas of higher peaked values. Clumping of these lighter areas are artefacts of the interpolation process. This is the result of an under and over sampling of the raw data creating erroneous interpolated artefacts in the surface. The subsequent second order derivative, slope, illustrates these artefacts, containing false highs in comparison to the other approaches. This should be noted as the artefacts could impact on a study of characterisation of landform morphology producing inaccurate results.

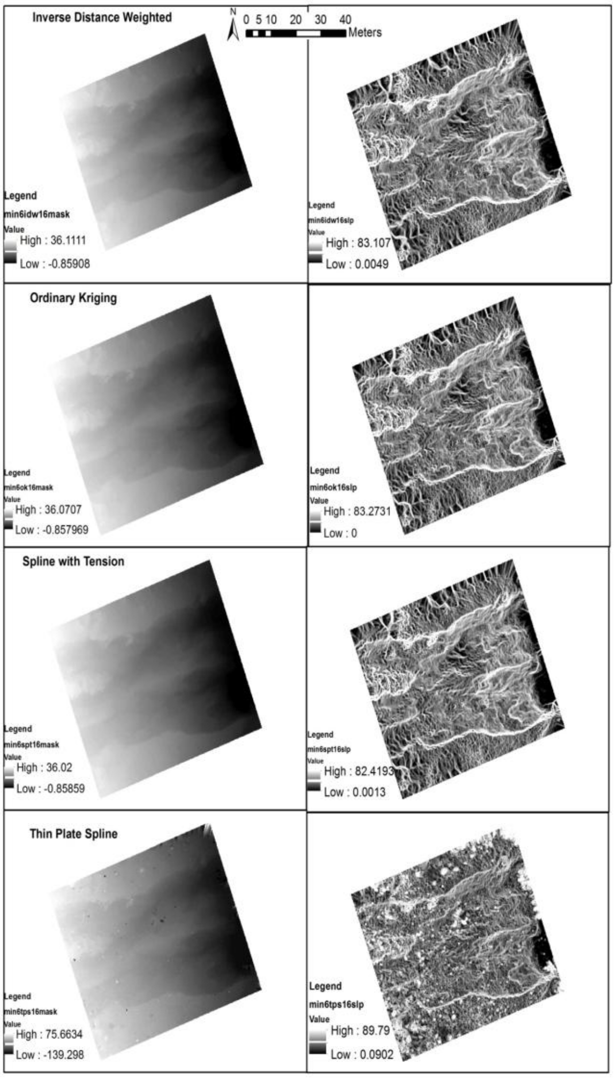

Figure 4: Multiple Interpolated DEMs with 16 neighbours. Left hand column is interpolated DEM and right column is the slope derived surfaces from the DEMs.

Advantages and limitations

Visual assessment of the interpolated DEMs highlights the potential error and the differences between the interpolation approaches. TPS, by the nature of the interpolation approach, makes predictions which are outside the range of the data values. Local small-scale variation in the dataset has produced a noisy output, a limitation of the TPS algorithm. The SPT counteracts this with the smoothing and tension parameters in the algorithm so that the predicted values are a closer fit to the actual raw survey data. This creates the lowest RMSE but not necessarily the best depiction of the raw survey data when analysing the output DEMs and statistics. Smoothing affects the interquartile range of the data and in some cases the maximum of the data is beyond the maximum values of the data. This can be detrimental when generating DEMs of highly variable terrain, as it can results in certain areas being cut off. Disadvantages of SPT and TPS are that the computation time is considerably longer than the other interpolation approaches, and as the RBFs interpolate outside of the domain of data they therefore have the potential to create artefacts and false highs or lows in the data.

The geostatistical approach using OK for interpolation produces a smooth output which has the second lowest average RMSE for multiple neighbours. The use of the locally varying mean within kriging is beneficial in generating an accurate representation of the elevation surface. However, kriging assumes a normal distribution and estimates the modelled variogram, which may not fit with the data used.

One of the benefits of the IDW approach is that it only predicts in the ranges of the input data. This is illustrated by the summary statistics and DEMs (Table 1; Figure 3 & 4). The neighbourhood becomes smoother as the moving window is increased which is displayed by a reduction in the RMSE. Lloyd and Atkinson (2002) suggest that the use of IDW is acceptable when the sample spacing is small, as it generally is for LiDAR datasets. The cross validation and statistics illustrate IDW as comparable to more complex approaches that generate a slightly smaller RMSE (Lloyd, 2007). IDW saves on computing time compared to more complex interpolation procedures. Disadvantages are the potential for the spikes or a 'duck egg' effect when there is a clustering of data points. 'Duck eggs' are characteristic high or low spots when IDW is giving greater weights to clustering of data sampling locations. Generally this is not an issue when using LiDAR data as it is overcome by the high resolution of data, but must be considered for other survey techniques.

Conclusion

This paper presents a method for determining the accuracy of interpolation approaches for generating DEMs. Examples of common interpolation approaches for generating surfaces from survey data are assessed through RMSE, spatial structure and Q-Q plots. Key findings indicate RMSE is a good indicator of error when assessing interpolation to DEMs. IDW is seen as a quick and easy exact interpolator and if used correctly, can be an effective means of generating DEMs from survey data. RBF are complex processor intensive functions and what is gained in some areas of the study can be lost in others with the potential for erroneous results to be higher. OK is similar to IDW in the production of the output surfaces and can be used if more control is required in the generation of the DEMs.

Results are dependant on survey data and site-specific conditions. This method provides the framework for the assessment of the interpolation approach discussing the advantages and disadvantages of each. Method presented can be applied to many environments and collected datasets. Researchers should investigate various interpolation approaches for generation of DEMs, choosing an appropriate tailored site-specific approach based on statistical information generated from the presented method.

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