A Comparative Study of Three Non-Geostatistical Methods for Optimising Digital Elevation Model Interpolation

Serajis Salekin, Jack H. Burgess, Justin Morgenroth, Euan G. Mason and Dean F. Meason

Abstract: It is common to generate digital elevation models (DEMs) from aerial laser scanning (ALS) data. However, cost and lack of knowledge may preclude its use. In contrast, global navigation satellite systems (GNSS) are seldom used to collect and generate DEMs. These receivers have the potential to be considered as data sources for DEM interpolation, as they can be inexpensive, easy to use, and mobile. The data interpolation method and spatial resolution from this method needs to be optimised to create accurate DEMs. Moreover, the density of GNSS data is likely to affect DEM accuracy. This study investigates three different deterministic approaches, in combination with spatial resolution and data thinning, to determine their combined effects on DEM accuracy. Digital elevation models were interpolated, with resolutions ranging from 0.5 m to 10 m using natural neighbour (NaN), topo to raster (ANUDEM), and inverse distance weighted (IDW) methods. The GNSS data were thinned by 25% (0.389 points m\(^{-2}\)), 50% (0.259 points m\(^{-2}\)), and 75% (0.129 points m\(^{-2}\)) and resulting DEMs were contrast against a DEM interpolated from unthinned data (0.519 points m\(^{-2}\)).

Digital elevation model accuracy was measured by root mean square error (RMSE) and mean absolute error (MAE). It was found that the highest resolution, 0.5 m, produced the lowest errors in resulting DEMs (RMSE = 0.428 m, MAE = 0.274 m). The ANUDEM method yielded the greatest DEM accuracy from a quantitative perspective (RMSE = 0.305 m and MAE = 0.197 m); however, NaN produced a more visually appealing surface. In all the assessments, IDW showed the lowest accuracy. Thinning the input data by 25% and even 50% had relatively little impact on DEM quality; however, accuracy decreased markedly at 75% thinning (0.129 points m\(^{-2}\)).

This study showed that, in a time where ALS is commonly used to generate DEMs, GNSS-surveyed data can be used to create accurate DEMs. This study confirmed the need for optimization to choose the appropriate interpolation method and spatial resolution in order to produce a reliable DEM.

Keywords: GNSS; ANUDEM; IDW; NaN; resolution; interpolation; DEM

1. Introduction

A digital elevation model (DEM) is a mathematically-derived representation of the Earth’s surface. It is produced by collecting elevation point data and then interpolating those points to a surface. There are several methods for capturing the data for DEM interpolation. For example, field surveys, photogrammetry techniques, radar, and aerial laser scanning (ALS) [1] have all been proposed. This latter method, also known as LiDAR (Light Detection and Ranging), using unmanned
airborne systems (UAS) or fixed-wing aircraft, has become the de facto standard for producing high-resolution DEMs [2–5]. This is because other data capture methods (i.e., the field survey) have several limitations—for instance, the coverage, time constraints, and accessibility. ALS, though, enables accurate measurement of elevation for a dense set of points on the Earth’s surface for a large area in a short time period. Moreover, LiDAR point elevations can have ±0.5 cm vertical and ±0.5 cm horizontal accuracy, and point densities typically between 0.5–50 points per square metre [6]. LiDAR point data are interpolated into a DEM, with typical spatial resolutions of <1 m.

Despite their accuracy, coverage, and efficient data capture, LiDAR acquisitions are costly and require expertise to analyse [7]. As such, LiDAR data are commonly only acquired for specialist land-based applications, including forestry [7], mining [8], agriculture [9], and urban planning [10]. However, even within these industries, the drawbacks of LiDAR acquisition and analysis can preclude their common use [5]. As such, there remains a need to explore less costly, simpler alternatives to DEM generation for many small-scale applications. Such alternatives would be especially useful in developing regions and small-scale areas, which for which LiDAR acquisitions are uncommon.

One such alternative, field surveying, can be used to describe topography. Field surveys using a global navigation satellite system (GNSS) receiver are methodologically simple. Since the initial launch of the global positioning system (GPS) in 1973 [11], GNSS have developed progressively, resulting in increased use by scientific communities and the general public. Improvements include a reduction in costs [12], improved positional accuracy, and precision [13]. Moreover, since GPS became fully operational in 1995, worldwide coverage has helped to ensure that GNSS surveying and mapping are possible in the world’s developing regions [14]. Point elevations are acquired across a landscape by a GNSS receiver and subsequently interpolated to a DEM, in much the same way as LiDAR data are interpolated into a DEM. GNSS (e.g., GPS, GLONASS, Beidou-2 Navigation Satellite System, and Galileo) and regional navigation satellite systems (e.g., Navigation with Indian Constellation (NAVIC)) are designed to estimate the geographic coordinates of a receiver by trilateration with three or more satellites. GNSS data are now commonly used for numerous applications requiring accurate positioning, including precision agriculture [15] and forestry [16], and surveying [17]. If GNSS elevation points are to be used to generate accurate DEMs, there remains a need to optimise various aspects of the process in order to minimise the error reported in previous studies [18].

Errors in digital elevation models are undesirable, especially because they can be perpetuated through derived topographic surfaces, including aspect, slope, hillshade, and surface curvature surfaces. Moreover, DEMs are critical in their role for normalising digital surface models, such that errors in a DEM will result in corresponding errors in digital surface models and canopy height models. Gong, et al. [19] grouped the factors which could influence the DEM quality into three classes: (i) accuracy, density, and distribution of the source data; (ii) characteristics of the surface; and (iii) the interpolation process. The accuracy of the source data varies with technique, such as LiDAR acquisition or field surveying. Density and sampling interval of the data can be modulated by experimental design, data collection decisions, and available time [20]. Besides these, the nature of the terrain also influences the quality of a DEM through natural uncertainty, as irregular surfaces can be more error-prone.

The third source of error is interpolation. Interpolation from elevation points to a surface can be achieved in many ways [21], thus introducing potential error into modelled elevation surfaces. The processes of creating a surface from either initial measured points (e.g., inverse distance weighted (IDW)) or the degree of similarity of the smoothed surfaces (e.g., Splines) are called non-geostatistical, or deterministic, methods. In contrast, geostatistical methods are based on statistics and probability [19,22,23]. A number of studies have been conducted to compare different interpolation methods, based on their end use to different disciplines [21,24–26]. Previous studies also include a comparison of accuracy based on different spatial attributes, such as slope, aspect, curvature and hydrologic process [20,22,27,28].

The main objective of this study was to evaluate the potential for generating a high-resolution DEM from data collected via a GNSS receiver during a field survey. This objective was achieved
by (i) comparing DEM accuracy for a range of spatial resolutions, (ii) comparing three different non-geostatistical interpolations, and (iii) examining the impact of data density on DEM quality.

2. Materials and Methods

2.1. Study Sites

A hilly broken landscape, covered by a young Eucalyptus spp. plantation, in the southern area of the Marlborough region, New Zealand, was selected for this study (Figure 1). The site (-41.7364606452187 latitude, 174.1221316582747 longitude) ranges in elevation from 10 m to 82 m above sea level (asl), has slope ranging from 13° to 32°, and covers 4.7 hectares. It has predominantly warm, dry, and settled weather during the summer months, with daytime maximum air temperature ranging from 20 °C to 26 °C, but occasionally rising above 30 °C. Winter days often start with a frost, but are usually mild overall, with daytime maximum air temperature ranging from 10 °C to 15 °C [29].

Figure 1. Location of the experimental site. Aerial imagery overlaid on a hillshade model.

2.2. Data Collection and Preparation

Positional data points were collected with Trimble® R8s real time kinetic geo-positioning system (RTK-GPS), by carrying a handheld receiver (“rover”) and establishing a base station for differential correction [13]. According to the manufacturer, the RTK-GPS has a theoretical horizontal accuracy of ±0.008 m + 1 ppm RMS, and a vertical accuracy of ±0.015 m + 1 ppm RMS [30]. However, a mean horizontal error of 0.014 m with standard deviation (SD) of 0.004 m, and a mean vertical error of 0.030 m with SD of 0.010 m were found under field conditions [4]. A total of 2722 data points were collected, over six hours, by walking transects across the site in a general east–west direction, at roughly 5 m intervals. The data collection was done on a clear sunny day to ensure minimum satellite distortion. At each point, coordinates (eastings, northings, and elevation) were recorded. All coordinates were georeferenced to the New Zealand Geodetic Datum 2000.

The train and test approach [31] was applied for quantitative evaluation of the GPS points. The collected data points were randomly partitioned into training (90%, n = 2440) and validation (10%, n = 282) datasets (Figure 2). The training dataset was randomly thinned by 25% (n = 1779),
50% \((n = 1220)\), and 75% \((n = 561)\) of its original point density (Figure 3 and Table 1), which ranged from 0.519 points/m² to 0.129 points/m² (Table 1).

![Elevation points diagram](image)

**Figure 2.** Layout of the collected data points.

**Figure 3.** Training points were thinned by (A) 0%, (B) 25%, (C) 50%, and (D) 75%.
Table 1. Summary of elevations resulting from different training data thinning intensities.

<table>
<thead>
<tr>
<th>Thinning (%)</th>
<th>Points</th>
<th>Elevations (m asl)</th>
<th>Point Density m⁻²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Min.</td>
<td>Max.</td>
</tr>
<tr>
<td>0</td>
<td>2440</td>
<td>9.749</td>
<td>82.139</td>
</tr>
<tr>
<td>25</td>
<td>1830</td>
<td>9.748</td>
<td>82.139</td>
</tr>
<tr>
<td>50</td>
<td>1220</td>
<td>9.748</td>
<td>82.139</td>
</tr>
<tr>
<td>75</td>
<td>610</td>
<td>9.765</td>
<td>79.495</td>
</tr>
</tbody>
</table>

2.3. Interpolation Methods and Parameters

Interpolation methods have been intensively studied for producing DEMs. Kidner [32] and Torlegård, et al. [33] reported two major research areas: (1) developing new interpolation methods and (2) optimising the selection of existing interpolation methods. There are a number of existing geographic data interpolation methods with various different approaches and uses [21,23]. Lam [34] categorised interpolation as either point or aerial methods. Shi and Tian [35] suggested linear, non-linear, and hybrid methods, while other authors have suggested various physically-based interpolation methods [36–39]. However, Li and Heap [40] broadly classified all interpolation methods into two main forms, namely deterministic and stochastic methods. Stochastic methods integrate the concept of randomness, and provide both estimations and associated variances and uncertainties. In a broad sense, stochastic methods are based on statistical properties of the data. Deterministic interpolation methods create surfaces from measured points based on either similarity or a degree of smoothing [21]. As such, deterministic methods are considered the simplest and easiest to apply. Here, three deterministic methods were compared for their potential to interpolate an accurate digital elevation model from different intensities of thinned training data.

The selected interpolation methods, as described below, were applied across all training datasets, to create DEMs with spatial resolutions ranging from 0.5 m to 10 m, increasing in 0.5 m increments. In total, 20 DEMs were interpolated. All the interpolations were carried out with the default setting in ArcGIS 10.4.1 [41]. The training DEMs were then evaluated against the validation dataset to assess the degree of agreement between each DEM and measured elevation.

2.3.1. Inverse Distance Weighted (IDW)

Inverse distance weighted (IDW) interpolation is an automated technique [42], requiring very few parameters from the operators [43]. It is specifically suitable where the dataset range is narrow and other fitting techniques are heavily affected by errors. The process is highly flexible and allows for the estimation of datasets with a trend or anisotropy [44].

IDW estimates cell values through a linearly weighted combination of sample points, where the weight assigned to each sample point is the inverse of its distance from the cell being estimated [42]. The underlying assumption of IDW is that an unsampled cell’s value is a weighted average of known cells’ data in the local neighbourhood [44]. The surface being interpolated should be that of a locally dependent variable, and each cell’s value is estimated as

\[
Z_j = \frac{\sum_{i=1}^{n} \frac{Z_i}{(h_{ijk}+\delta)^\beta}}{\sum_{i=1}^{n} \frac{1}{(h_{ijk}+\delta)^\beta}}
\]

where \(Z_j\) is the unsampled location value, \(Z_i\) is the known cell’s value, \(\beta\) is the weight, and \(\delta\) is the parameter. The separation distance \(h_{ijk}\) is measured by a three-dimensional Euclidian distance:

\[
h_{ijk} = \sqrt{(\Delta x)^2 + (\Delta y)^2 + (\Delta z)^2}
\]
where \( \Delta x \) and \( \Delta y \) are the distances between the unknown and known point according to the reference axes, respectively, and \( \Delta z \) refer to the height as the third point of measure.

### 2.3.2. Topo to Raster

Topo to raster (ANUDEM) interpolation is a morphological approach designed for scattered surface-specific point elevation data and stream line data. The input data may include point elevations, elevation contours, streamlines, sink data points, cliff lines, boundary polygons, lake boundaries, and data mask polygons. It attempts to take into account the special nature of the terrain surfaces, and the surface specific points that can be used for the sample terrain [45]. The topo to raster model is considered by many studies to produce hydrologically correct DEMs (e.g., [46,47]).

### 2.3.3. Natural Neighbors (NaN)

The natural neighbors (NaN) interpolation method was introduced by Sibson [48]. The model works by finding the nearest subset of samples for a given cell without a measured value, and then applies weights to the samples based on the proportional area they occupy [48]. In other words, it combines features from both nearest neighbours (NN) and triangular irregular network (TIN) interpolation methods. It starts with a triangulation of the data by Delaunay’s method, and then finds adjacent samples by Thiessen polygons. The value of an unknown cell is estimated by inserting and determining the point within a polygon. For each neighbour, the area of the portion of its original polygon that becomes incorporated in the tile of the new point is calculated [49]. This method is well known for its ability to interpolate scattered and unevenly distributed data [50].

### 2.4. Analysis

For evaluation purposes, a set of statistical calculations was carried out (Table 2), following Willmott [51], Vicente-Serrano, et al. [52], and Li and Heap [40] in an R statistical environment by using base packages [53]. These include the coefficient of determination (\( r^2 \)) from the ordinary least square (OLS) model; the bias of the model, as indicated by the intercept–slope pair; the mean bias error (MBE); the mean absolute error (MAE); and the root mean square error (RMSE). MAE and RMSE are the best overall measures for evaluating agreement between observed and predicted data [40,52,54]. Both are similar metrics, except the RMSE is more sensitive to extreme outliers, whereas MAE is less so. To overcome that sensitivity, we include model efficiency (EF), which is based on the relationship between observed and predicted mean deviations [55]. EF values closer to 1 specify model reliability.

<table>
<thead>
<tr>
<th>Statistical features</th>
<th>Definitions</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N ) = number of observations</td>
<td></td>
</tr>
<tr>
<td>( O ) = observed value</td>
<td></td>
</tr>
<tr>
<td>( O' ) = mean of observed value</td>
<td></td>
</tr>
<tr>
<td>( P ) = predicted value</td>
<td></td>
</tr>
<tr>
<td>( P_i' = P_i - O' )</td>
<td></td>
</tr>
<tr>
<td>( O_i' = O_i - O' )</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Ordinary least square regression</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r^2 ) = coefficient of determination</td>
<td></td>
</tr>
</tbody>
</table>

| Mean bias error (MBE) | \( MBE = \frac{\sum_{i=1}^{N} P_i - O_i}{N} \) |
| Root mean square error (RMSE) | \( RMSE = \sqrt{\frac{\sum_{i=1}^{N} (P_i - O_i)^2}{N}} \) |
| Mean absolute error (MAE) | \( MAE = \frac{\sum_{i=1}^{N} |P_i - O_i|}{N} \) |
| Model efficiency (EF) | \( EF = 1 - \frac{\sum_{i=1}^{N} (P_i - O_i)^2}{\sum_{i=1}^{N} (O_i - O')^2} \) |
In addition to statistical metrics, a subjective evaluation was also undertaken to evaluate the different interpolations. As Daly, et al. [56] highlighted, empirical knowledge can help to determine which method best reflects reality, so long as those methods produce reasonable statistical values. As a result, following the statistical evaluation, DEMs were visually assessed for their agreement with the original landscape.

3. Results

3.1. Digital Elevation Model Resolution Analysis

All the DEM resolutions yielded very high $r^2$ values, ranging from 0.9946–0.9995 (Table 3). The 0.5 m resolution produced the DEM surface with highest $r^2$ value (0.9995) and $r^2$ values decreased with a reduction in resolution, reaching 0.9946 at 10 m resolution. This result was reinforced by the RMSE and MAE being lowest for the 0.5 m resolution DEM (Table 3 and Figure 4), and increasing steadily from 0.429 m to 1.38 m and from 0.274 m to 1.088 m for the RMSE and MAE, respectively, at 10 m resolution. The MBE, which indicates the bias of the prediction, showed that at or below resolutions of 5 m the DEMs underestimated elevation slightly, whereas at coarser resolutions (specifically at 5.5 m, 8 m, 8.5 m, 9 m, and 10 m), the DEMs generally overestimated elevation. Moreover, the EF (0.999 > 0.994) for 0.5 m resolution was closer to 1 compared to lower resolutions, which indicates being in line with other findings, irrespective of any of the three selected methods.

Table 3. Results of statistical analysis for different digital elevation models (DEM) resolutions.

<table>
<thead>
<tr>
<th>Resolution</th>
<th>$r^2$</th>
<th>Slope</th>
<th>Intercept</th>
<th>RMSE (m)</th>
<th>MAE (m)</th>
<th>MBE (m)</th>
<th>EF</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>0.9995</td>
<td>1.0042</td>
<td>−0.2155</td>
<td>0.428</td>
<td>0.274</td>
<td>0.029</td>
<td>0.999</td>
</tr>
<tr>
<td>1</td>
<td>0.9904</td>
<td>1.0051</td>
<td>−0.2604</td>
<td>0.450</td>
<td>0.308</td>
<td>0.036</td>
<td>0.999</td>
</tr>
<tr>
<td>1.5</td>
<td>0.9994</td>
<td>1.0042</td>
<td>−0.2114</td>
<td>0.455</td>
<td>0.325</td>
<td>0.024</td>
<td>0.999</td>
</tr>
<tr>
<td>2</td>
<td>0.9993</td>
<td>1.0039</td>
<td>−0.2213</td>
<td>0.488</td>
<td>0.363</td>
<td>0.049</td>
<td>0.999</td>
</tr>
<tr>
<td>2.5</td>
<td>0.9992</td>
<td>1.0053</td>
<td>−0.2654</td>
<td>0.532</td>
<td>0.409</td>
<td>0.029</td>
<td>0.998</td>
</tr>
<tr>
<td>3</td>
<td>0.9991</td>
<td>1.0049</td>
<td>−0.2438</td>
<td>0.571</td>
<td>0.447</td>
<td>0.024</td>
<td>0.998</td>
</tr>
<tr>
<td>3.5</td>
<td>0.9989</td>
<td>1.0027</td>
<td>−0.1715</td>
<td>0.616</td>
<td>0.484</td>
<td>0.051</td>
<td>0.998</td>
</tr>
<tr>
<td>4</td>
<td>0.9989</td>
<td>1.0048</td>
<td>−0.2549</td>
<td>0.615</td>
<td>0.485</td>
<td>0.040</td>
<td>0.998</td>
</tr>
<tr>
<td>4.5</td>
<td>0.9987</td>
<td>1.0077</td>
<td>−0.3825</td>
<td>0.697</td>
<td>0.548</td>
<td>0.044</td>
<td>0.998</td>
</tr>
<tr>
<td>5</td>
<td>0.9984</td>
<td>1.0064</td>
<td>−0.3156</td>
<td>0.758</td>
<td>0.606</td>
<td>0.033</td>
<td>0.998</td>
</tr>
<tr>
<td>5.5</td>
<td>0.9982</td>
<td>1.0077</td>
<td>−0.3316</td>
<td>0.804</td>
<td>0.648</td>
<td>−0.009</td>
<td>0.997</td>
</tr>
<tr>
<td>6</td>
<td>0.998</td>
<td>1.0020</td>
<td>−0.1096</td>
<td>0.830</td>
<td>0.656</td>
<td>0.021</td>
<td>0.997</td>
</tr>
<tr>
<td>6.5</td>
<td>0.9976</td>
<td>1.0056</td>
<td>−0.2718</td>
<td>0.91</td>
<td>0.744</td>
<td>0.024</td>
<td>0.997</td>
</tr>
<tr>
<td>7</td>
<td>0.9974</td>
<td>1.0057</td>
<td>−0.3005</td>
<td>0.968</td>
<td>0.789</td>
<td>0.050</td>
<td>0.996</td>
</tr>
<tr>
<td>7.5</td>
<td>0.9966</td>
<td>1.0094</td>
<td>−0.4256</td>
<td>1.103</td>
<td>0.889</td>
<td>0.011</td>
<td>0.996</td>
</tr>
<tr>
<td>8</td>
<td>0.9965</td>
<td>1.0049</td>
<td>−0.1730</td>
<td>1.108</td>
<td>0.877</td>
<td>−0.044</td>
<td>0.995</td>
</tr>
<tr>
<td>8.5</td>
<td>0.9957</td>
<td>1.0032</td>
<td>−0.1151</td>
<td>1.228</td>
<td>0.991</td>
<td>−0.026</td>
<td>0.995</td>
</tr>
<tr>
<td>9</td>
<td>0.9953</td>
<td>1.0034</td>
<td>−0.0916</td>
<td>1.276</td>
<td>1.030</td>
<td>−0.060</td>
<td>0.994</td>
</tr>
<tr>
<td>9.5</td>
<td>0.9945</td>
<td>1.0030</td>
<td>−0.1725</td>
<td>1.384</td>
<td>1.107</td>
<td>0.040</td>
<td>0.994</td>
</tr>
<tr>
<td>10</td>
<td>0.9946</td>
<td>1.0062</td>
<td>−0.1957</td>
<td>1.380</td>
<td>1.088</td>
<td>−0.077</td>
<td>0.994</td>
</tr>
</tbody>
</table>

Figure 4. Effect of resolution at each observation point by (A) RMSE (root mean square error) and (B) MAE (mean absolute error).
3.2. Interpolation Methods and Data Density

GPS points were thinned by 25%, 50%, and 75%, and interpolated into three DEMs with 0.5 m resolution, using each of the three different interpolation methods. Thinning had little effect on $r^2$ relative to the DEM produced from the complete set of data points (0% thinned) (Table 4). Even with 75% thinning, the $r^2$ values only decreased to 0.999, 0.9952, and 0.9984 for the natural neighbor (NaN), inverse distance weighting (IDW), and Topo to raster (ANUDEM) methods, respectively. NaN had the lowest levels of bias at 25% (MBE = 0.004 m) and 50% (MBE = −0.015 m), while at 75% thinning, IDW exhibited the least bias (MBE = 0.029 m).

Table 4. Comparison of the three methods at 0.5 m resolution with different data densities.

<table>
<thead>
<tr>
<th>Method</th>
<th>Thinning (%)</th>
<th>$r^2$</th>
<th>Slope</th>
<th>Intercept</th>
<th>MBE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural Neighbour (NaN)</td>
<td>0</td>
<td>0.9995</td>
<td>1.004</td>
<td>−0.216</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>0.9998</td>
<td>1.001</td>
<td>−0.090</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>0.9997</td>
<td>1.003</td>
<td>−0.140</td>
<td>−0.015</td>
</tr>
<tr>
<td></td>
<td>75</td>
<td>0.999</td>
<td>1.009</td>
<td>−0.370</td>
<td>−0.059</td>
</tr>
<tr>
<td>Inverse Distance Weighting (IDW)</td>
<td>0</td>
<td>0.9989</td>
<td>1.004</td>
<td>−0.269</td>
<td>0.059</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>0.9982</td>
<td>1.014</td>
<td>−0.730</td>
<td>0.116</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>0.9952</td>
<td>1.027</td>
<td>−1.238</td>
<td>0.029</td>
</tr>
<tr>
<td></td>
<td>75</td>
<td>0.9998</td>
<td>1.005</td>
<td>−0.284</td>
<td>0.024</td>
</tr>
<tr>
<td>Topo to Raster (ANUDEM)</td>
<td>0</td>
<td>0.9996</td>
<td>1.010</td>
<td>−0.489</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>0.9998</td>
<td>1.005</td>
<td>−0.282</td>
<td>0.022</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>0.9984</td>
<td>1.024</td>
<td>−1.046</td>
<td>−0.044</td>
</tr>
</tbody>
</table>

Given the high $r^2$ values, it is unsurprising that generally the observed and predicted values were in agreement (Figure 5). The observed and predicted values of the data points were slightly more scattered in the DEM, interpolated using IDW. Figure 5 also shows that the spread of the residuals increased when elevation data were thinned by 75% prior to DEM interpolation.

RMSE and MAE data provide better opportunities to discriminate between different interpolation algorithms with thinned data. IDW yielded the highest RMSE and MAE, irrespective of the level of data thinning applied (Figure 6). For IDW, RMSE ranged between 0.631 m and 1.388 m, and MAE ranged between 0.471 m and 0.984 m. In contrast, NaN and ANUDEM interpolations resulted in lower RMSE and MAE values at all thinning intensities. RMSE ranged between 0.239 m and 0.614 m and between 0.305 m and 0.877 m for NaN and ANUDEM, respectively, while MAE ranged between 0.152 m and 0.301 m and between 0.197 m and 0.526 m. Irrespective of interpolation algorithm, RMSE and MAE remained reasonably consistent until 75% thinning, when there was a large increase in both metrics. At 75% thinning, the density of the points used to interpolate the DEM was only 0.129 points m$^{-2}$, compared with 0.519 points m$^{-2}$ in the un-thinned data.

In addition to quantitative analyses, a visual inspection was carried out on the DEMs produced by the three interpolation methods. It was found that the IDW produced a less reliable surface, with a lot of abnormalities (Figure 7(C0–C3)). In contrast, the NaN and ANUDEM produced more consistent and representative DEM surfaces. Moreover, among the two, ANUDEM interpolated the DEM surface, both with consistency and reliability, in relation to the original surface (Figure 7(B0–B3)). It resembled reality more closely, where NaN produced a surface that was overly smooth and unrealistic (Figure 7(A0–A3)). With greater elevation data density, the surface better resembled the original natural surface, showing features like mounds or gullies—whereas, with the reduction of elevation data points through thinning, the surface was rendered relatively smoothly, and topographic features that were visible with higher data densities were obscured. For example, a gully on the site was virtually invisible with the lowest data density (i.e., 75% thinning) (Figure 7(A3,B3,C3)).
**Figure 5.** Residuals plotted against predicted elevation (m) for different models and levels of data thinning. Red line shows the model prediction trend.

**Figure 6.** Comparison of three interpolation method in regards of different data density: (A) root mean square error (RMSE) and (B) mean absolute error (MAE).
4. Discussion

4.1. An Alternate Data Source

The GNSS-surveyed elevation point data can be used to produce a high-resolution DEM. Though aerial laser scanning data are commonly used for this purpose, their shortcomings may preclude their use in some instances. In contrast, collecting elevation data via GNSS surveys is inexpensive and easy to undertake, often with little or no specialist skill. The data density of ALS yields high accuracy and resolution [57,58]. However, depending on the desired DEM resolution, the high point density associated with ALS data may not be needed [57], suggesting that the relatively low elevation data density achievable with a GNSS approach may be appropriate under some conditions; however, this will depend on the required resolution and the interpolation used to generate the DEM.

4.2. Optimal Resolution

Spatial resolution is important for DEMs, as many other surfaces can be derived from it. Errors in a DEM are perpetuated through to derived aspect, slope, hill-shade, and surface curvature surfaces, amongst many others. Moreover, DEMs are critical in their role for normalising digital surface models. In this study, errors in the DEM were minimized by increasing spatial resolution from 10 m to 0.5 m. This finding is in line with previous research showing that DEMs interpolated from LiDAR point clouds had accuracy proportional to spatial resolution [59–61]. Although those results were based on LiDAR data, which typically has much greater point density than the point density achieved with the GNSS approach, in this study, the underlying theory remains the same.

4.3. Influencers of Digital Elevation Model Quality

The question of resolution and DEM accuracy is also dependent on the characteristics of the surface being modelled [26,59,62]. Flat surfaces can be interpolated accurately even with relatively few elevation points due to topographic homogeneity. In contrast, surfaces that are topographically heterogeneous are likely to require greater point density and higher resolution, in order to capture small undulations or other features in the landscape.
Data density and distribution have also been shown to influence interpolation quality \cite{22,63}. The present study clearly shows that elevation point density influenced DEM quality. At low densities, a small number of data points were used for interpolation, creating a generalized surface; this was because most of the deterministic approaches are mainly based on some simple mathematical functions \cite{22}. Li and Heap \cite{23} reported that data distribution had a greater effect, relative to data density, on the quality of the DEM produced.

On the contrary, it is not suitable to produce high-resolution DEMs from sparse data, as the surface will be shaped by the proliferated interpolator and interpolation artefacts \cite{58,64,65}, as well as the resolution constraints designated by the data density \cite{66}. For this study, all the data were collected in a way that was assumed to give an evenly distributed dataset. Hence, the effect of distribution was not tested explicitly. Moreover, the selection of validation points, thinning, and study site characteristics would have resulted in some spatial variation in point distribution. Firstly, the validation points had high positive spatial correlation with the training dataset as they were not independently collected and lying in line with each other. Secondly, even though the thinning routine was performed in a randomised manner, minor clustering may have influenced the results. Thirdly, the study site was relatively small. Hence, it is expected that the results are site specific and could vary with changes in site or surface structure. For example, if the site were more rugged than the one used here, a higher level of error could be expected.

4.4. Deterministic Interpolation Method

The interpolation method is important for the accuracy of the interpolated digital elevation model, because interpolation can vary with the nature of the surface terrain and spatial structure \cite{26,62,67}. In the present study, though, ANUDEM and NaN had similar quantitative metrics: ANUDEM produced a more realistic and consistent DEM, relative to the NaN interpolation. NaN is mostly used in cases where there is a need to have a geo-morphologically smooth surface \cite{68}, whereas ANUDEM tends to be useful where well-defined drainage and major topographic features exist \cite{45}. It is important to note that there is no single optimal interpolation method, but rather many methods optimized by matching them with particular end uses of the DEM \cite{69}. This is further supported by Arun \cite{62} and Kienzle \cite{59}, who stated that the interpolation method is mostly chosen based on the purpose and focus of the research. The implication of this research and previous studies is the importance of testing various interpolation algorithms for individual sites, in order to create a guide through the process of obtaining an optimised one.

5. Summary and Conclusions

This study evaluated the quality of digital elevation models interpolated from elevation data acquired from a differentially corrected GNSS (RTK-GPS) receiver. Three interpolation methods (NN, IDW, and ANUDEM) were compared, as was the influence of different spatial resolutions and data densities. With dense and regularly distributed data, a high-resolution DEM (0.5 m) was interpolated, with RMSE value 0.428 m and MSE value 0.274 m. Thinning the elevation point data by 25% or even 50% had minimal effect on the DEM quality. Despite similar quality from a quantitative perspective, ANUDEM performed better than NN- and IDW-interpolated DEMs from a qualitative perspective. In this study, the use of quantitative and qualitative approaches for judging DEM quality resulted in a better decision.

LiDAR data acquisition has become the standard approach for collecting point data to interpolate high-resolution ground and above-ground surfaces (e.g., canopy height model). LiDAR acquisition is generally only cost-effective over large contiguous areas of land. The present results are promising for applications where it is unfeasible to acquire LiDAR data. The RMSE and MAE values are higher than those from LiDAR studies \cite{70}, but are within an order of magnitude, and therefore comparable. In conclusion, the interpolation of data collected via GNSS surveys can yield accurate digital elevation models. This method should be considered alongside LiDAR data interpolation as a
viable means of generating topographic surfaces, especially in cases where study areas are small and easily accessible. In these areas, the GNSS approach can provide a low-cost, efficient, and effective solution for DEM creation.


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