Vertical accuracy assessment of LiDAR ground points using minimum distance approach

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Abstract

Light Detection And Ranging is now being widely used to provide accurate digital elevation model (DEM). One common method used to determine the accuracy of LiDAR - Light Detection And Ranging - vertical accuracy is compared LiDAR-derived DEM elevation with survey-derived ground control points (GCPs). However, because the DEM elevations are generalised to the areas covered by one cell, inherent errors when compared to the elevation of a GCP are evident. This paper presents a method based on a minimum distance approach using the so called first law of geography to assess the accuracy of LiDAR ground point dataset. The result has shown that the tested LiDAR ground point dataset is suitable for applications that do not need a vertical accuracy better than 0.5m.

1 Introduction

The Victorian Government in Australia has embarked upon a program, called “Future Coast”, which involves acquiring vertical heights along the Victorian coast using Airborne Light Detection and Ranging, or LiDAR. The intent of this program is to construct detailed digital elevation models (DEMs) for the littoral zone from the high tide water level inland up to an elevation of ten metres. Therefore the inland horizontal extent of this data set varies due to the irregularities in the coastal topography, involving venturing only several metres inland on cliffs and stretching up to several kilometres on low-lying land. The metadata that comes with the dataset claims a vertical accuracy of 0.1 metres (DSE, 2010).

Aguilar et al. (2010) state that the best achievable realistic vertical accuracy in open terrain is around 0.15 metres. A similar result has been reported by Hodgson and Bresnahan (2004). However, this level of accuracy can rarely be achieved (Aguilar et al.,2010). Although LiDAR has been acquired for the specific needs of the Future Coast project in Victoria, there are demands for using just LiDAR data for various applications, ranging from research to public resource management (Hodgson et al.,2005). There is a need to convey the limitations of the LiDAR data to end users. This is a global issue, not limited to Victoria, Australia.

An accurate topographic dataset is important for supporting decisions in water resource management. Local governments, who are responsible for local flood management, can use LiDAR for drainage design in the context of stormwater and overland flood management. Whilst the accuracy of the LIDAR acquired heights has been reported by the Future Coast project, there are concerns regarding the vertical accuracy of LiDAR dataset in different regions.

The accuracy of LiDAR depends on the full workflow from data acquisition through to the final derived DEM. During acquisition, the accuracy of positioning using the Inertial Measurement Unit (IMU) located on the aircraft, and the on-board Global Positioning System receiver (GPS) will inform the accuracy of the point clouds acquired. These devices establish the position of the platform, and then the lasers measure distances at different angles. Multiple returns are possible from objects in the landscape, including vegetation, buildings and bare ground. Errors or bias can be introduced during LiDAR point cloud segregation when a filtering process to separate ground and non-ground points is applied. Most of these effects introduce systematic errors that are non-

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normally distributed and exhibit kurtosis and skewness in their distribution. According to Aguilar and Mills (2008) the nominal stated accuracy for LiDAR elevations quoted by vendors assumes a normal distribution and are typically derived from limited checks. It would seem more prudent to present accuracy with a lower and upper Root-Mean-Square-Error (RMSE) at a specific confidence level.

This present is a study which examines the vertical accuracy of LiDAR ground point data using survey permanent marks. The accuracy is determined using the Root Mean Square Error (RMSE). However, RMSE is sensitive to the outliers, and the skewness and the kurtosis effect of non-normal error distribution (Zandbergen,2008). Therefore, a robust measure is preferred where error distribution is not normal (Höhle and Höhle,2009). The present study uses the statistical method which includes the upper limit of the RMSE value in order to account for the skewness and kurtosis effects on the final accuracy assessment.

The remainder of this paper is organised as follows. Firstly, a brief overview of airborne LiDAR technology and a short background about LiDAR data vertical accuracy assessment is presented. The remainder focuses on a case study area and the sources of available elevation data. The methodological section introduces the used datasets for this study, the workflow used to compare GCPs and LiDAR ground point dataset, and the statistics have been used to assess LiDAR vertical accuracy.

2 Airborne LiDAR 3D point cloud

The basic operation of a LiDAR survey involves some platform (airplane, helicopter or terrestrial vehicle) which carries the LiDAR instrument that sends out a laser pulse and records a distance and (optionally) reflected intensity at each angle. Therefore, LiDAR technology is considered an active remote sensing which actively transmits pulses toward target areas as shown in Figure1(Wehr and Lohr,1999).

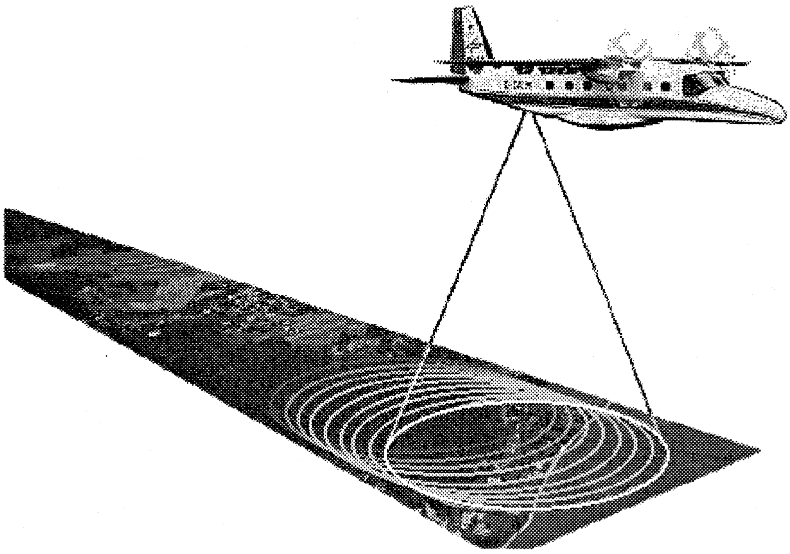


Figure 1. LiDAR footprints (Wehr and Lohr,1999)

The footprint characteristics of the LiDAR reflected pulses are controlled by beam divergence and flying height (distance from target). The usual commercial beam divergence is between 0.2 and 0.8mrad giving a footprint size between 0.2m and 1.10m at a one kilometre flying height (Lemmens,2011). Ground locations for LiDAR are obtained from post processing of Differential Global Navigation Satellite System (DGNSS) data or directly in real-time, through the integration of LiDAR data with GPS data (Habib et al.,2005). Data is collected in terms of latitude, longitude, and ellipsoidal height based on the reference ellipsoid,WGS1984. Then the acquired data needs to be transformed to the formally accepted regional or national horizontal and vertical datum before further use. The vertical or height datum represents the ortho-metric height value while GPS height is the ellipsoidal height value(Liu et al.,2007).

Acquiring LiDAR reflected pulses can be either discrete or in full waveform. Discrete pulse returns are captured at two or more vertical levels depending upon the ground characteristics. Crowns of trees can return one pulse at one level, whilst the ground will return a pulse at a lower elevation.

Since 2008, Multiple LiDAR Pulse in Air (MPiA) LiDAR has been used, whereby a larger ground area can be covered, or lower flying heights can be used, without reducing spatial resolution. Flying at lower altitudes results in lower air turbulence. Therefore MPiA enables LiDAR data to be acquired more cheaply than traditionally acquired LiDAR data (Lemmens et.al (2011); Mallet and Bretar (2009). The result of these surveys is termed a point cloud, since it takes further processing to turn the raw results into a surface model for a particular purpose.

3 Background into determining LiDAR vertical accuracy

The accuracy, and in particular vertical accuracy, of LiDAR is highly dependent on errors of parameters such as flying height, location (from on-board GPS) and inertial measurement units (IMU) errors, distance to ground station and LiDAR post-processing (Hodgson and Bresnahan,2004; Hodgson et al.,2005).The common method used to determine the relative vertical accuracy of LiDAR derived elevations is to compare the LiDAR-derived DEM against ground control points (GCP) (Maune et al. 2007).

The GCP points can be permanent survey marks or GPS points. Besides the common accuracy assessment using LiDAR-derived DEM (Maune et al.,2007), GPS points can be surveyed at exact location of interest LiDAR points according the approach suggested by Hodgson and Bresnahan (2004). Furthermore, it is possible to extract GCP values for points of interest using all surrounding LiDAR points. The latter approach was used to develop a tool by Webster and Dias (2006). Re-measuring the LiDAR points by accurate GPS is time consuming and labour-intensive while using the tool developed by Webster and Davis (2006) is fast and user-friendly. Survey marks which have already been established as a basis for determining the coordinate position of spatial datasets are used to reduce time and effort. Furthermore, using a sufficient number of check point with proper spatial distribution across study area is required to undertake a LiDAR data accuracy assessment. Thirty points are deemed to be the minimum requirement for each prominent land cover across a study area according to the American Society for Photogrammetry and Remote Sensing (ASPRS) and ICSM (Inter-Governmental Committee on Surveying and Mapping) (ICSM,2008). Hodgson et al. (2003) claim that LiDAR data accuracy varies for different land cover conditions. It is also claimed that LiDAR data accuracy in flat areas are twice as accurate as those in steeper landscapes with forest coverage (Hodgson et al.,2003). ASPRS (Flood,2004) and ICSM (ICSM, 2008) guidelines have separated the vertical accuracy assessment into three land categories in order to accurately assess LiDAR vertical accuracy. Three major categories for accuracy assessment include open terrain suitable to support fundamental vertical accuracy (FAV), areas covered by various land cover to support the supplemental vertical accuracy (SVA), and combined land cover area to support consolidated vertical accuracy (CVA). It is assumed that FAV has the highest accuracy in estimating terrain surface height value due to there being limited barriers for LiDAR pulses. LiDAR vertical accuracy assessment can be reported at 95% confidence level by 1.96(RMSE) for FAV and 95th percentile for SVA and CVA. Regarding to report accuracy assessment, the ICSM (2008) has recommended that the 95th percentile value of accuracy should be adhered to for FAV, SVA, and CVA. However, Liu (2011) claimed that the accuracy value reported by of 95th percentile overestimates vertical accuracy in compare with vertical accuracy reported by 1.96(RMSE).

4 The study area

The test study was conducted for the Bass Coast Shire council area lying approximately 130 kilometres to the south-east of Melbourne, Victoria, Australia. This area is experiencing unprecedented population growth due to many people wanting to retire close to the sea, as well as general regional pressures. The Bass Coast Local Government Area had the highest growth rate in Victoria between 2001 and 2006 of around 21 precent (Buxton, 2008). Growth has highlighted the need for appropriate development in what is a predominantly a low lying coastal plain. The area is exposed to rainfall from frontal systems from the Southern Ocean. The coastal area is also fed overland by mountainous terrain to the north. All drainage water for this area flows into Bass Strait (Figure 2). Developers' requests to subdivide new estates within Bass Coast Shire Council's jurisdiction are increasing. Two important policy documents control water resources management for the Bass Coast Shire Council. Land use control is managed through the Bass Coast Flood Management Plan and the Integrated Water Management plan (formerly the Stormwater Management Plan).

Figure 2: Inverloch test site in Bass Coast Shire Council (Source: Bass Coast Shire Council)

The digital representation of a terrain surface which is the core dataset in hydrological modelling and flood management, is available through elevation data resources in Victoria, Australia. VICMAP, a digital resource of natural and cultural features covering the entire state of Victoria, provides the most comprehensive coverage of elevation data, DEM. Each DEM file has a 20m by 20m cell size, with the cell value interpolated from digital contours at 20 meters spacing on a map series at 1:25000. One source of elevation is the LiDAR dataset. However, LiDAR is not provided for the whole state. The LiDAR dataset as a reliable method for acquiring 3D data is useful because of its higher resolution as well as its vertical accuracy. LiDAR-derived DEMs applications are various, for example, they are suitable for extracting detailed overland flow paths, refined catchment boundaries and providing a better estimation of hydrographs for hydrological modelling.

5 Methodology

The goal of this work is to assess the vertical accuracy of the Future Coast LiDAR bare-ground points dataset in the given study area. This requires the collection and preparation of observed elevations and the GCPs. Common comparisons can be made using an interpolation technique for transforming sample elevation points into a DEM (gridding method), then comparing the cell value to a corresponding GCP such as survey permanent marks (PMs). The gridding method introduces error due to the influence of averaging elevations over a given cell.

Interpolating elevations derived by LiDAR, to determine unknown heights, will ultimately depend upon the interpolation method used, including the input parametres such as neighbouring distance and the effect of direction (anisotropy).

An alternative approach is to undertake a one-to-one comparison between the LiDAR ground points height and the elevation derived from GCPs. This approach was used by Hodgson et al. (2003). This approach is suitable to accurately compare heights because errors introduced through gridding are eliminated. However, the method is time-consuming.

The third approach is use a proximal point algorithm suggested by Webster and Dias (2006). In this method the user determines a search radius around target GCPs. This automatically produces minimum, maximum and other statistical values relating to the GCPs and the LiDAR dataset comparison. The values for the heights of the GCPs are compared to the results from interpolation of LiDAR points for a defined buffer around the GCPs. Although the proximal approach facilitates the comparison between the LiDAR dataset and the GCPs, it uses an interpolation technique to estimate GCPs height values and compare on a one-to-one basis between the LiDAR and the GCP elevation values. Furthermore, there are no rules to limit the search distance.

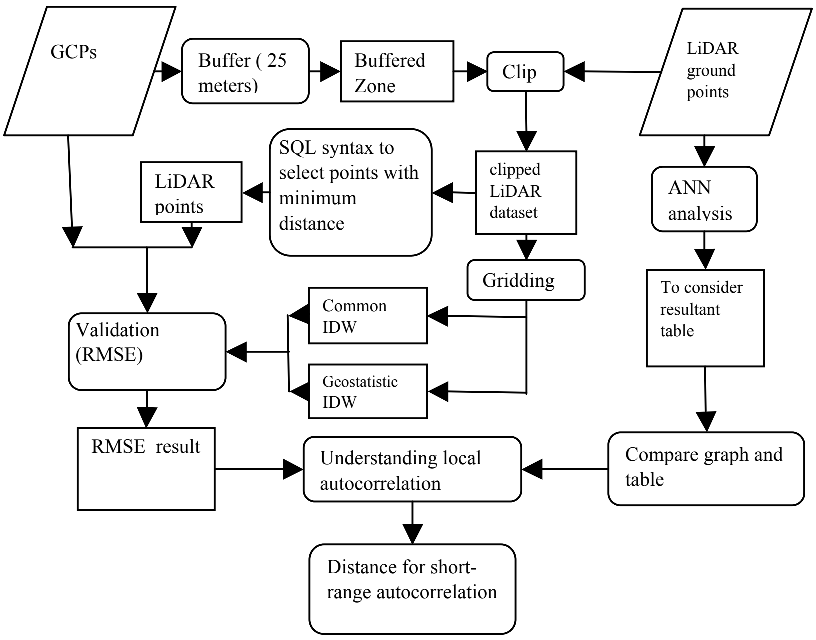
In order to overcome the search radius problem and avoid imposing gridding errors into the procedure, the solution is to undertake a one-to-one comparison between the GCPs and the LiDAR sample points using a autocorrelation distance (minimum distance) based on Tobler's first law of geography (Tobler,1970). This can be used to assess vertical accuracy of LiDAR dataset. Therefore, the LiDAR ground points within a spatially autocorrelated distance (closer features are similar) should represent similar height values as the GCPs. This approach has been used in this study.

Although the search distance can be manually defined by user, increasing the search distance will result in the number of elevations being compared and therefore relevant processing time will increase. It also results different RMSE values. One metre distance has been chosen for proximity analysis in this study. One metre selected due to the common pixel size used in the LiDAR-derived DEM. Within the one meter search distance, those points which are located at the first minimum distance from the checkpoints selected are compared, then the points that are located at the second, third and fourth sequential minimum distances have been chosen and compared using a separate comparison procedure.

The present study also takes the autocorrelated distance using average nearest neighbour analysis (ANN) and compared derived distance with the distance, which shows the lowest RMSE, extracted from proposed method developed for this study, the sequential minimum distance.

Another comparison has been done using GCPs and DEM derived from LiDAR ground points at 25m around each GCPs using common Inverse Distance Weigh (IDW) and geostatistic IDW interpolation techniques to define the influence of interpolation methods on LiDAR DEM vertical accuracy.

Flow chart 1 shows the work flow steps used in this study. Flowchart 1 also shows the process from which it is possible to find the relation between the difference in value and short-range autocorrelated distance. Short-range autocorrelation distance represents the distance over which it is expected that LiDAR points have the lowest difference to GCPs.



Flowchart 1. Present study workflow

6 LiDAR dataset

The test data was selected for an area around the township of Inverloch. This area was selected because new residential development is permitted in the urban fringe area, the availability of data, and the importance of the area in a local flood management plan. The test data was sourced from the Future Coast program provided to the Bass Coast Shire Council by the Victorian Government Department of Environment and Primary Industry (DEPI). The data consisted of LiDAR points covering a two kilometre by two kilometre area. The vertical accuracy (DSE, 2010) is stated as +/- 0.10m with 68% confidence, with the positional accuracy being +/- 0.35m.

Data was projected on the Geocentric Datum of Australia 1994 (GDA94) and elevations defined by the Australian Height Datum (AHD). The data had been captured in 2007 and has been accessible to users since 2009.

7 Ground Control Points (GCPs)

Ground control points such as survey permanent marks (PMs), that have previously been established for elevation and position, using conventional surveying and levelling techniques, were used to assess the accuracy of LiDAR ground point dataset. The suitability of PMs in Victoria was discussed in Liu (2011). Liu (2011) stated that 80% of PMs in rural area have vertical accuracy better than +/- 0.20m and 90% of PMs in Township area have vertical accuracy better than +/-0.03m due to the greater accuracy requirements and therefore greater survey accuracies applied for urban PMs. PMs have a density of 0.63 marks per square kilometre in Victoria. This is around ten times the density for other Australian states (Liu,2011). Figure 3 shows the geographic location of 85 PMs that were available throughout the study area.

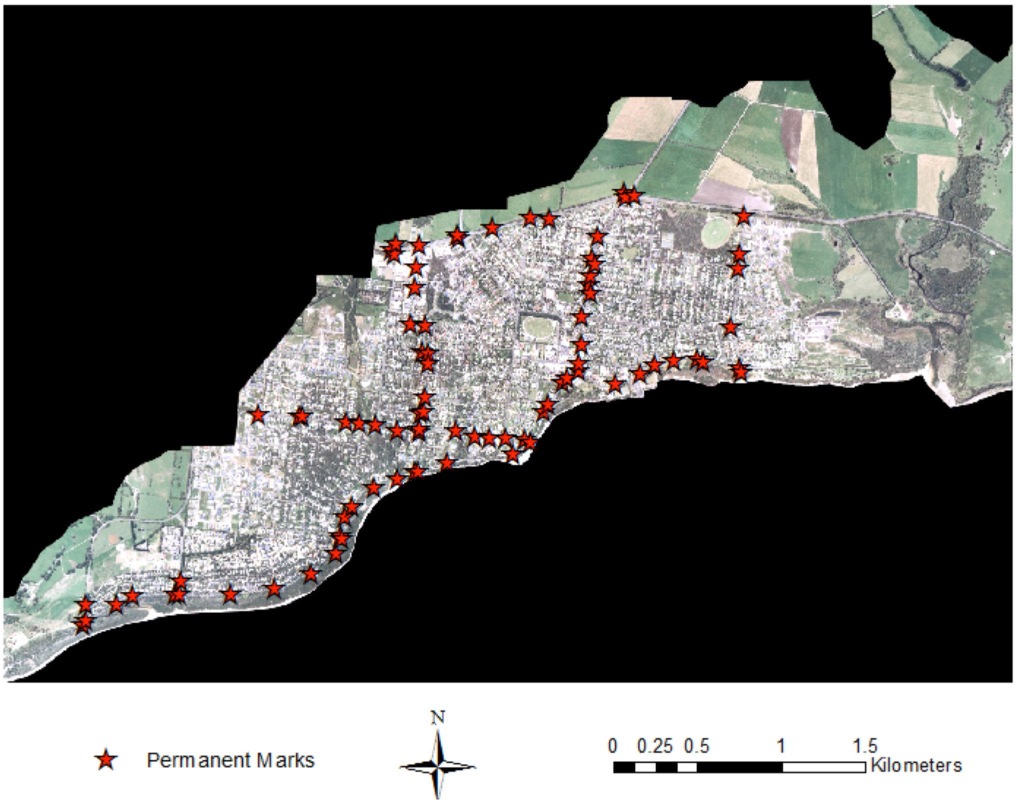


Figure 3: Permanent Survey Marks location in Inverloch, Victoria, Australia (Source: Bass Coast Council's GIS database)

8 Statistics for vertical accuracy assessment

Root Mean Square Error (RMSE) is a frequently used measure to understand overall accuracy assessment (Carlisle,2005). Furthermore, Aguilar and Mills (2008) have suggested using the upper and lower RMSE error for showing the range of error instead of representing only the average error value by RMSE. The upper and lower limits show the influence of kurtosis and skewness of error distribution. This gives the end user an appreciation of the range of error each vertical value may have. This means the effect on non-normal distribution of error can be included in accuracy assessment. Equations 1 to 3 show RMSE, RMSE upper (worst accuracy) and RMSE lower.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Z_{model(i)} - Z_{check(i)})^2}{n}} \tag{1}$$

$$RMSE_{lower} = \sqrt{mse - \frac{\frac{\gamma_{2mse}+2}{\gamma_{1mse}} - \sqrt{\left(\frac{\gamma_{2mse}+2}{\gamma_{1mse}}\right)^2 + \left(4\left(\frac{t_\alpha\sqrt{(\gamma_{2mse}+2)(\gamma_{2mse}+2-\gamma_{1mse}^2)}}{|\gamma_{1mse}|}+1\right)\right)}}{2}\sigma_{mse}} \tag{2}$$

$$RMSE_{upper} = \sqrt{mse + \frac{\frac{\gamma_{2mse}+2}{\gamma_{1mse}} - \sqrt{\left(\frac{\gamma_{2mse}+2}{\gamma_{1mse}}\right)^2 + \left(4\left(\frac{t_\alpha\sqrt{(\gamma_{2mse}+2)(\gamma_{2mse}+2-\gamma_{1mse}^2)}}{|\gamma_{1mse}|}+1\right)\right)}}{2}\sigma_{mse}} \tag{3}$$

Where mse is mean square error , σ_{mse} is the mse standard deviation, γ_{1mse} shows mse skewness and γ_{2mse} is mse standardised kurtosis, t_α is statistical t-student test. For further information on equation parameters, see Aguilar and Mills (2008); Aguilar (2005); Aguilar and Aguilar (2007).

9 Analysis

For the test LiDAR data in Inverloch, each PM was buffered by 25m, then LiDAR ground points were clipped inside each buffer to reduce the LiDAR points to be processed(Figure 4). Distance to each PM was calculated for all LiDAR ground points within 1m around PMs. RMSE values were estimated based on individual comparing between elevation values of LiDAR points located in first, second, and subsequent minimum distances from each PMs. RMSE value for each minimum distance considered to identify the distance where RMSE start to increases due to reduces of similarity. Short-range autocorrelation distance, alternatively, can be determined by average nearest neighbour (ANN) analysis.

The RMSE value was then estimated by including all LiDAR points located in 1m from PMs in order to identify the influence of averaging technique occurring in gridding process. The one metre distance was chosen due to the typical cell size in the existing LiDAR-derived DEM for the study area. Finally, RMSE values were estimated between LiDAR DEMs - derived using Inverse Distance Weight (IDW) and Geostatistic IDW interpolation methods - and PMs using the suggested method by ASPRS (Flood,2004) and ICSM (ICSM, 2008) to identify the influences of used interpolation techniques.

Figure 4: The LiDAR dataset in each buffer around PMs

10 Results

Using the procedure described in section 9, the accuracy assessment between LiDAR points and PMs. Table 1 shows the results that have been extracted through the analysis.

Table 1: Resultant RMSE for the minimum distance at different distances around PMs. N^i shows i^{th} minimum distance

	Average distance (m)	RMSE	Upper-RMSE
N^1_Minimum	0.366	0.241	0.377
N^2_Minimum	0.625	0.257	0.410
N^3_Minimum	0.980	0.259	0.413
N^4_Minimum	1.252	0.270	0.428
Combination of N^1 to N^4	1	0.259	0.373
IDW	1	0.228	0.364
Geostatistic IDW	1	0.249	0.398

The first column in Table 1 shows the average distance from each PMs. The second and third columns show the RMSE and Upper-RMSE (worst accuracy) for each individual comparisons. Results in Table 1 show that the closest LiDAR ground points to the PMs (0.366m) have the lowest value of RMSE (0.241). The RMSE increases from the second minimum distance. Combining the value for all LiDAR points with a minimum distance to PMs and calculating the RMSE value shows a 0.259 for the RMSE. Using two Inverse Distance Weight (IDW) and geostatistic IDW interpolation techniques to estimate the value for PMs has shown that using the simple common IDW technique represents the lowest value RMSE (0.228) while the geostatistic IDW method has shown a RMSE equal to 0.249. The result of this research shows that the geostatistic IDW-derived DEM with one square metre spatial resolution gives a better estimate of elevation for the study area than common IDW, which leads to underestimate derived elevation error. The inherent error in the LiDAR ground point dataset expected to be increased in developed DEM.

Due to error normal distribution (Figure 5), vertical accuracy is estimated using 1.95*RMSE at a 95 percent confidence level (Flood,2004). Normality checks on the error distribution has been conducted using the Kolmogorov-Smirnov test. Assuming a value of 0.259 for RMSE, the vertical accuracy value for LiDAR ground points in the test area is around 0.5m. Furthermore, this study shows that the vertical accuracy in the common IDW-derived DEM with one metre by one metre pixel size is around a 0.444m, which is more accurate than the original LiDAR dataset with 0.5m vertical accuracy.

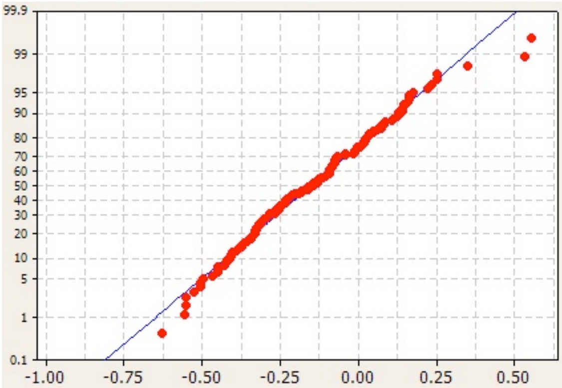


Figure 5: The sample of Q-Q plot to show error normal distribution

As mentioned earlier, PMs were used as a control for determining the accuracy for observed LiDAR elevations. However, it has been pointed out by Liu (2011) that determining the corresponding elevations for PMs from LiDAR data is critical for accuracy assessment. It is largely accepted that elevation is a geographic phenomenon that adheres to Tobler's first law of geography (Tobler,1970), that is, "Everything is related to everything else, but near things are more related than distant things." This is often referred to as "autocorrelation". However, a geographic distance, or "neighbourhood distance" from those control points, that can be used for estimating the accuracy of LiDAR observations, needs to be determined. Lag size is required to determine long-range autocorrelation based on an empirical semivariogram for a given dataset. However, proper lag size is also needed to determine the short-range autocorrelation.

Comparing the result of the ANN (Table 2), it has been shown that ANN can be used to determine an appropriate distance to identify autocorrelated neighbour LiDAR points. Table 1 shows that the RMSE value between 0m and 0.366m gives the lowest amount the RMSE. It can be concluded that the highest similarity between LiDAR point and PMs occurs within 0m-0.625m (average in 0.366m) around each PMs. Resultant outcomes from the ANN analysis (Table 2) shows that the lowest RMSE occurs between 0m and 0.531m distance from PMs due to the short-range autocorrelation, which is similarity between LiDAR points and PMs. Thus, instead of a comparison between LiDAR sample points and PMs in sequential minimum distances distance, ANN can be applied to show the short-range autocorrelation distance between LiDAR ground points and PMs.

The study area is influenced by anisotropy in long-range autocorrelation (Figure 6), the short-range autocorrelation within 0.531 meters has been assumed to be isotropic.

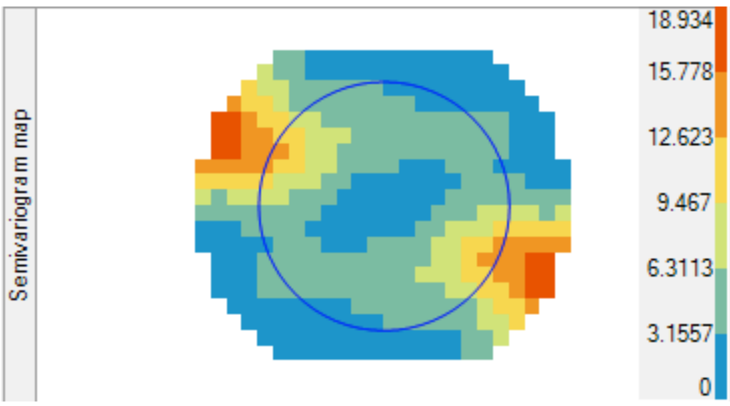


Figure 6: Anisotropy influences on derived empirical semivariogram using 500 random stratified derived sample points in a given LiDAR dataset.

Figure 6 shows the southwest-northeast directional effect, calculated from a sample of 500 points drawn as a stratified random sample of the LiDAR dataset. The noted direction (pathway) is because of the orientation of the coastline and the change from flat areas to more rugged surface in the opposite direction, southeast-northwest.

Table 2: Statistical results of the ANN analysis for given LiDAR dataset

Ratio	*P*-value	Expected(m)
1.262	<0.0001	0.531

Table 2 shows the result of the ANN analysis. Short-range autocorrelation can be represented in the lag-size being equal to expected distance. A ratio score more than 1 shows that the distribution of sample points are not clustered, therefore the resultant vertical accuracy is valid for the LiDAR ground points which are not within 0.531m around PMs. Furthermore, P-value less than 0.0001 shows 99% confidence level in estimated vertical accuracy.

11 Conclusion

This paper has presented an alternative method of determining the accuracy of a LiDAR dataset. The approach was based upon a comparison between LiDAR ground points and PMs in sequential minimum distance. This approach enables LiDAR vertical accuracy assessment studies to avoid gridding influence on the final vertical assessment. The Table 1 shows that 0.366m from PMs results the lowest RMSE.

Furthermore, autocorrelation distance has been defined using an ANN analysis. The analysis shows that 0.531m around each LiDAR point is expected the similarity distance for each LiDAR point. The 0.531m is similar with the distance where the value of the RMSE changes from 0.241 to 0.257 in Table 1.

To determine the extent to which vertical accuracy is subject to interpolation methods, LiDAR DEMs derived from common IDW and geostatistic IDW were considered. Result shows that LiDAR DEM derived from geostatistic IDW presents elevation close to the real ground elevation in study area.

The vertical accuracy resulted from comparing between LiDAR ground point and PMs in autocorrelated distance is around 0.5m at 95% confidence level. Therefore, the LiDAR ground point dataset can be used for applications that do not need the vertical accuracy to be better than half a metre in the given study area.

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