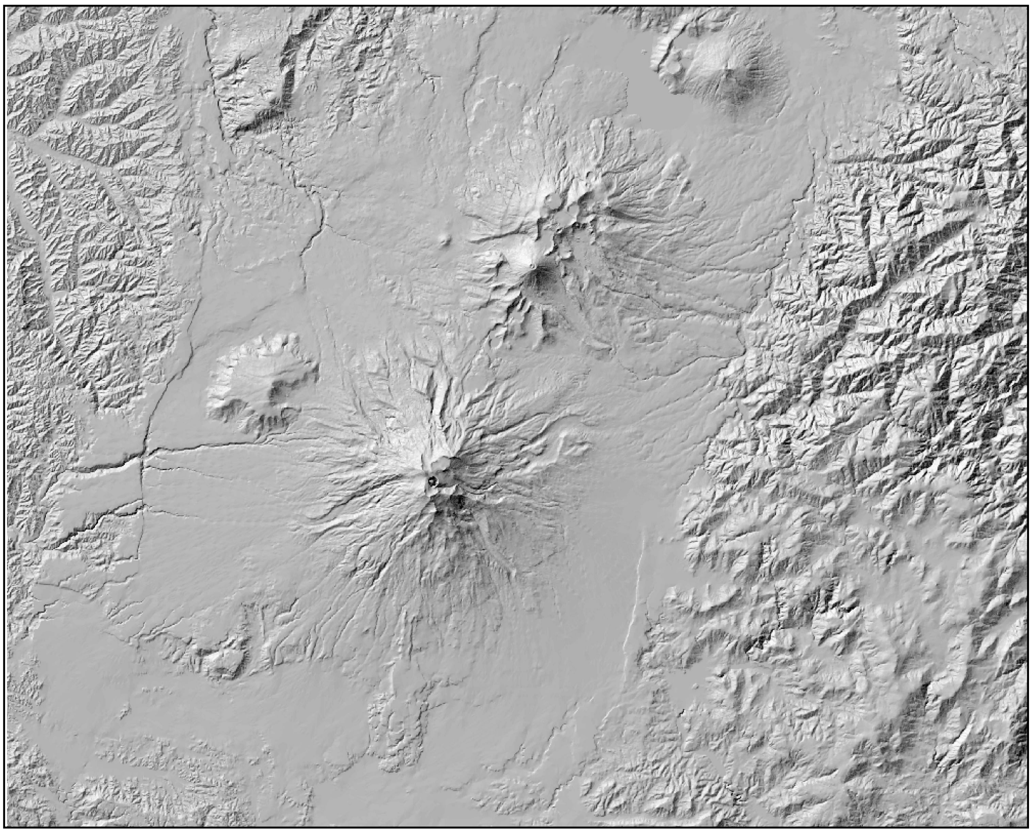
# DEVELOPMENT OF A HIGH-RESOLUTION

# DIGITAL ELEVATION MODEL

# FOR NEW ZEALAND



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Landcare Research Contract Report: LC0102/170

PREPARED FOR:
Foundation for Research, Science & Technology
P.O. Box 12-240, Wellington, New Zealand

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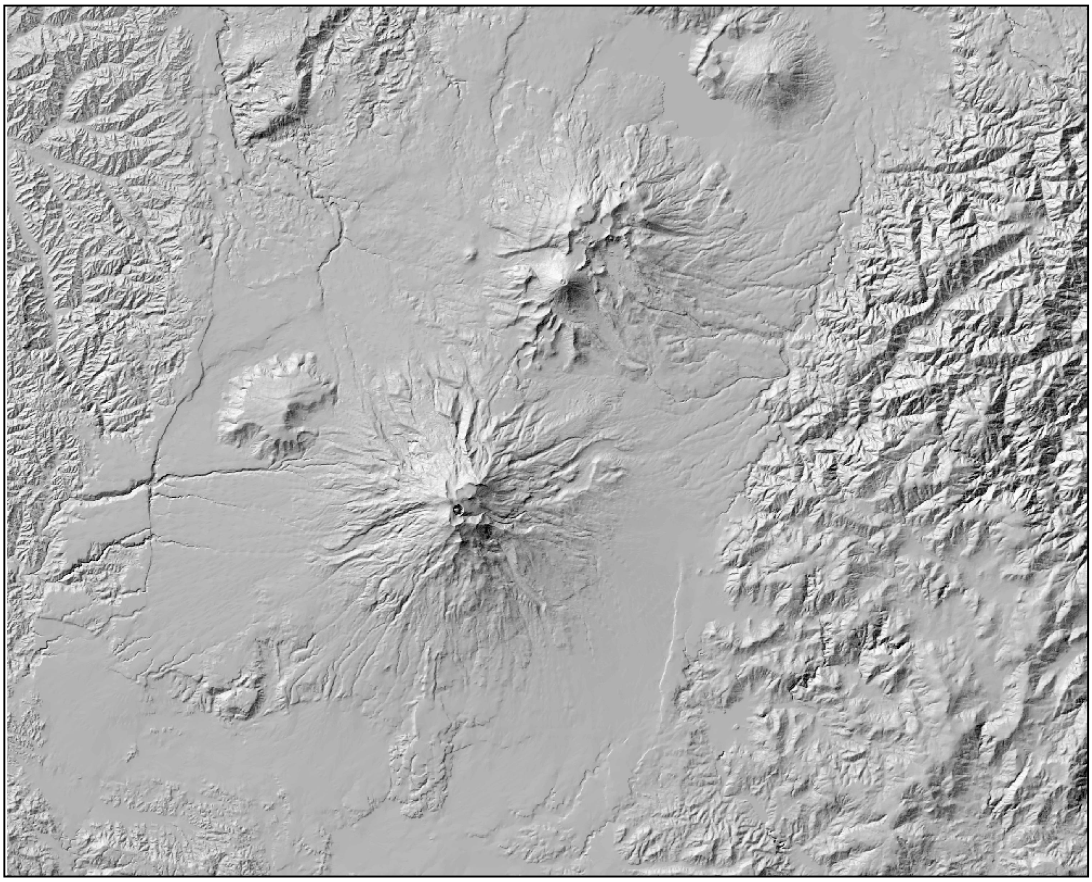

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# Contents

## Summary


### Project and Client

This is a report on progress by Landcare Research in developing a high-resolution digital elevation model of New Zealand from the national TOPOBASE data supplied by Land Information New Zealand (LINZ), as required by the Foundation for Research, Science and Technology.

### Objective

- To generate an improved DEM for New Zealand and describe the method used, state any assumptions underpinning its generation, and provide suitable accuracy information so that potential users can take uncertainty into account.

### Methods

- Version 2 of the DEM had a number of important changes to the interpolation algorithm to resolve problems that arose in version 1. These changes included: interpolating from up to four contours or spot heights instead of two, assigning the pixel height based on interpolation within the pixel, tracking distances from the nearest contours using floating point precision and allowing diagonal steps, and using floating point precision for elevations in the final DEM. We are considering further improvements to resolve remaining problems that affect our goal for absolute elevation correctness.
- We tested our DEM against a very high-resolution reference DEM (LIDAR points of 2.5m average posting and approximately 0.25m vertical accuracy) filtered through a finite impulse response (FIR) filter designed to suppress data at spatial frequencies other than the desired 25 m.
- We attempted to predict spatial variability of RMS error in relation to landform complexity based on existing land classifications, e.g. New Zealand Land resource Inventory.

### Results

- The filtered LIDAR reference DEM indicated a consistent bias in our national DEM that overestimated elevation by a mean of approximately 6 m. A previous GPS-based analysis in a different area indicated a bias of <0.5 m. Filtering the LIDAR reference DEM indicated that RMS error is actually less, and almost halved the standard deviation of errors.
- Spatial accuracy of our DEM in relation to landform complexity (based on the NZLRI and a detailed landform classification) was poorest in river valleys, but this was a terrain type not included in our previous GPS analysis so we are unable to compare the two analyses directly.

**Conclusions**

- Our national DEM meets internationally acceptable accuracy standards as set out by the US Geological Survey.
- Errors in the DEM are likely to be found at the local scale as pockets of ill-fitting terrain data related to landform.
- While the spatial accuracy of the national DEM varies between landforms, areas of greatest error are confined predominantly to valley floors.
- Global estimates of DEM error are of limited value and it is at least necessary to have landform-based error estimates and preferable to have a detailed error surface.

**Recommendations**

- Investigate further improvements to resolve remaining problems that affect our goal for absolute elevation correctness. These include: generating a set of pseudo spot heights to occupy the centre of closed contours representing hilltops without any spot height currently defined, and introducing streamlines as additional input data with elevations of vertices along the streamline interpolated between the points at which the streamlines cross contours.
- Acquire sufficient LIDAR reference data to adequately sample a full range of landforms so as to generate a comprehensive error surface based on the distribution of landforms.
- Test other DEMs generated by other organisations and/or using different software to compare and contrast accuracy and utility of DEMs for various applications.

# 1. Introduction

This report outlines progress in developing a high-resolution (1:50 000 scale – 25 m cell size) digital elevation model of New Zealand from the national TOPOBASE data supplied by Land Information New Zealand (LINZ). This process has been enabled by changes in copyright policy by LINZ, which has freed up access to the TOPOBASE digital topographic data. As a result, a number of public and private organisations have developed regional or national digital elevation models (DEMs) at resolutions ranging down to 25 m. With modern GIS software and adequate computer hardware it is a relatively straightforward process to develop high-resolution DEMs using off-the-shelf tools. However, while some DEMs available for public use contain obvious errors, few of these large-area DEMs carry with them a clear indication of overall accuracy such as a root mean square error (RMS) statistic, let alone any comprehensive assessment of the spatial variability of DEM accuracy. In addition, there is a range of different interpolation methods available for deriving DEMs (e.g., bilinear interpolation, various spline functions, radial basis functions, and geostatistical methods like kriging). Each method has its advantages and disadvantages, and may be more fitted to particular types of use (e.g., hydrological analysis versus ortho-rectification of satellite imagery). There is no right way to generate a DEM, but what is important is to ensure that the method used is properly described, and that any assumptions used are clearly stated, and suitable accuracy information is provided with the DEM so that users can take uncertainty into account when using the data, or can post-process the DEM for use for specific purposes (e.g., filling pits for hydrological analysis). This is particularly the case given the rapidly growing trend for using sophisticated Monte Carlo techniques for incorporating uncertainty (based on error distributions) into spatial modelling using DEMs.

This report for FRST describes the process LandcareResearch used to generate a national DEM in 2002, and our progress on utilising GPS and a very high-resolution reference DEM from LIDAR data (2 m), to set a standard for reporting the accuracy of our national DEM to potential users.

# 2. Building the National DEM

To generate a raster DEM from a vector set of contours, we must first define an interpolation process. The objective of such an interpolation is to define a height at each grid position in the raster image that best represents the surface defined by the contours. Unfortunately, the best surface representation is somewhat dependent on the intended use of the DEM. Therefore different interpolation methods may be preferable depending on the end use.

## 2.1 Interpolation method for Landcare Research 25-m DEM

Landcare Research has produced a national DEM at 25 m postings to be consistent with the 20-m contours and spot height information available from LINZ. The aim in producing this DEM has been absolute elevation correctness and speed of interpolation, rather than hydrological correctness, slope continuity, or some other performance goal. Version 1 of the

DEM produced had integer precision, but subsequently we have produced a version 2 with floating point precision. Version 2 also had a number of important changes made to the algorithm to resolve some problems that became apparent during the construction of version 1.

The interpolation process was based on work carried out by David Giltrap (pers. comm.) for use in a VAX computer system. Initially we ported this code to a SUN UNIX environment. The Giltrap algorithm was based on the idea that for any regular and complete set of contours, any region will be bounded by contours of at most two different levels (Fig. 1). The interpolator he developed makes use of this contour topology by (without crossing contours) using a neighbourhood expansion process to grow into the regions bounded by contours while keeping track of the minimum distance to two different contour levels. Once the neighbourhood process has been completed, each pixel within the region will have the minimum distances to the bounding contours at two different levels (or one if bounded by a single contour elevation). The height assigned to the point is a ratio of these two levels in inverse proportion to the minimum distance found. This method ensures that both bounding contour levels affect the whole region bounded, even if no line can be drawn from a point to one of the bounding contour levels without crossing the other contour. Thus, valleys are not flattened out even when obscured from the lower contour (Fig. 1).

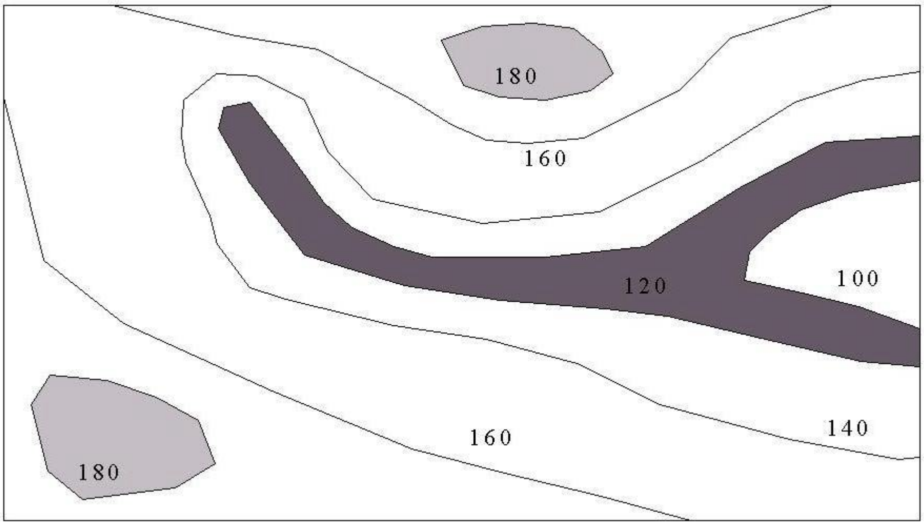



**Fig. 1** All areas are bounded by two contours apart from those in light grey, which are bounded by only one. The whole of the dark grey region is interpolated between 100 and 120 m, even the neck of the valley obscured from the 100-m contour.

Unfortunately the introduction of mid-slope spot heights and non-regular contours (e.g., lake shorelines) break the topology described above and introduce a third height adjacent to the area being interpolated. As result, artefacts in the surface could be found where the set of two nearest heights changed. To overcome this problem we modified the procedure to keep track of up to four contours or spot heights adjacent to an area being interpolated. This fixed the problems observed with mid-slope spot heights or lake shorelines creating artefacts in the DEM surface.

In the original UNIX implementation if a contour passes through a DEM pixel, then that pixel was set to the contour level. A contour was considered to have passed through the pixel if it entered the diamond connecting the midpoints of the pixel's four sides, or if it had a node within the pixel. If more than one contour passed through the pixel, then the level assigned was that of the contour passing closest to the pixel's centre. In this latter case, care was taken to interpolate from the contours nearest the pixel's boundaries, irrespective of which contour was used to assign the pixel value.

It became apparent from analysis of version 1 of the DEM that, by assigning pixel values to contour values where contours met the criteria for passing through the pixel described above, in steeper areas the DEM would have a high proportion of pixels that had elevations that had been assigned not interpolated. This meant the old algorithm had a tendency to assign pixels to multiples of 20 m or 10 m when contours were dense with respect to the posting distance. In version 2 of the DEM, instead of assigning a pixel with a contour running through it, to the value of that contour (or the one running closest to the centre), our new algorithm keeps track of the contours running closest to each of the pixel's four edges and assigns the pixel height based on an interpolation within the pixel.

Finally where the old algorithm tracked distances as multiples of cell size (i.e., 25 m) in the four primary directions, in the new algorithm the distances of points from the four nearest contours are tracked more accurately using floating point precision in distance measures and allowing diagonal steps.

## 2.2 Interpolator implications

The interpolation method described above results in some undesirable DEM characteristics that users should be aware of:

1. Hilltops without a spot height will be flattened at the level of the highest contour, as the region within that contour only has a single adjacent elevation to interpolate from.
2. Slope continuity is not maintained across contours or spot heights.
3. Valleys tend to have a slight stepping in the longitudinal profile because distances to contours marking the side of the valley are less than contours crossing the valley floor. This means the interpolation process overestimates valley height mid-way between each set of 'cross contours'.

While some of the above characteristics are not aesthetically pleasing, they are unlikely to have a great impact on the overall absolute accuracy of the DEM. The first two will only affect small areas within the DEM. Enforcing slope continuity or other constraints such as hydrological correctness can in fact reduce absolute accuracy.

## 2.3 Future improvements

We are, however, considering options for resolving these outstanding problems:

1. It may be possible to generate a set of pseudo spot heights to occupy the centre of closed contours representing hilltops without any spot height currently defined.
2. We will introduce streamlines as additional input data with elevations of vertices along the streamline interpolated between the points at which the streamline crosses a pair of contours.

# 3. DEM Accuracy Assessment

Few DEMs carry with them a clear indication of overall accuracy such as a root mean square error (RMS) statistic, let alone any comprehensive assessment of the spatial variability of DEM accuracy. Comprehensive measures of DEM accuracy are extremely important because they can be used to calculate the uncertainty of terrain parameters derived from the DEM, such as slope, aspect, and curvature, as well as providing the basic information for quantitative estimates of errors in drainage maps, shade maps, etc.

There are a number of important criteria that need to be met in order to provide an independent assessment of DEM accuracy (Wood 1996). First, reference elevation data must be independent of the DEM generation process. Second, reference elevation data must be representative of the terrain. Third, if spatial estimates of accuracy are to be made, then they must be done within a framework of common spatial variability (i.e., with the same or similar spatial frequency characteristics). Unfortunately, while these criteria are easy to state, they are often difficult to satisfy. For example, a common strategy is to withhold certain data from the DEM generation process, and use the withheld data as ground truth (United States Geological Survey 1997). Withholding data degrades the accuracy of the DEM, and the most commonly used reference information (i.e., spot heights) may not provide a good sample of landscape positions to test DEM accuracy over a fully representative surface (Kumler, 1994). Furthermore, the input data also contain errors that are not always well described. For example LINZ state that their topographic data have a planimetric (x,y) accuracy with 90% of well-defined points within ±22 m; and a vertical (z) accuracy with 90% of well-defined points within ±5 m, and contour lines within ±10 m (LINZ 2002). However, what constitutes a ‘well defined’ point is not explained, so as a statement of data accuracy it is not useful when attempting to estimate the errors in, say, slope maps. In effect, DEM accuracy estimates derived using withheld input data as ground truth may only tell us how well we have converted our input data to DEM format, not how accurately the DEM represents the real land surface.

More recently some researchers have utilised the satellite global positioning system (GPS) to provide truly independent ground truth data with sub-metre data accuracies that are approximately an order of magnitude better than medium-resolution photogrammetric data, and on a par with the accuracy of surveyed points (e.g., Barringer & Lilburne 1997; Carlisle 2000). However, like traditionally surveyed spot-height data it is difficult to collect substantial amounts of ground truth data to properly test the accuracy of a DEM surface. GPS data have also been used in estimating spatial variability of DEM accuracy (Carlisle 2000). Although when applied globally statistics such as RMS error are not particularly sensitive to localised DEM error, Carlisle developed regression models for creating an RMS surface using correlations with a variety of terrain parameters.

## 3.1 Comparing the reference DEM to contour-based DEM

To determine the accuracy of the national DEM generated from contours using the method outlined above, height information is required that has a quality that is known to be at least as good as the DEM under test. Spot heights provide little information about the spatial characteristics of a DEM at a wide range of scales, since the spatial density of spot heights is not sufficiently great. We therefore chose to check the national DEM against a reference high-resolution DEM. Since the contour-derived national DEM represents the finest scale for which we have dense whole-country data, it is necessary to select higher-resolution DEMs of selected regions. Necessarily, this approach assumes that the higher-resolution DEM has characteristics that are indicative of more general regions in the landscape, rather than having characteristics that are unique to one region, for it would be difficult to generalise the results of the comparison if this were not the case.

As a first attempt at an accuracy assessment, we have chosen to use LIDAR data as the reference dataset, although the methods described here are applicable to all reference DEM sources. The LIDAR data used in this analysis were gathered as a series of *(x,y,z)*-points, with an average sample spacing of 2.5 m, and an approximate vertical accuracy of 0.25 m (Jonas 2001). These LIDAR points were then made into a triangulated irregular network and rasterised to form a DEM with a spatial resolution of 2 m, in the same projection as the contour DEM (Fig. 2).

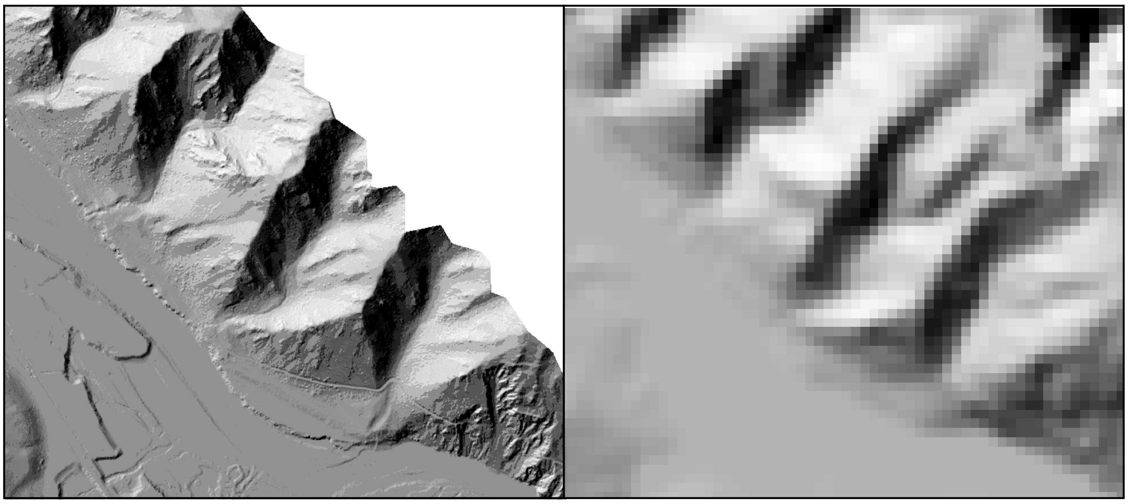


**Fig. 2** On the left is a shade map of an area of approximately 1.5 km$^2$ showing the 2-m resolution LIDAR data compared with the same area of the 25-m national DEM at right. While the major ridges and valleys are clearly visible in both shade maps, the LIDAR data holds a great deal more information, both in the river valley where low terraces and even gravel bed features can be identified, and on the steeper hill slopes where rock outcrops, gullies and vehicle tracks are clearly visible.

## 3.2 Comparison methodology

Unless the reference DEM happens to have been gathered at exactly the same spatial scale as the contour-based DEM, one of the DEMs needs to be resampled to match the other. When the contour-based DEM is resampled to match the resolution of the reference DEM, a straightforward sample-by-sample comparison is not valid, since the high-resolution DEM contains information at high spatial frequencies that are not present in the lower-resolution contour-based DEM. It does not make sense to compare these two DEMs as-is, since the key task is *to estimate the accuracy of the contour DEM at the spatial scale at which it is generated*. For this reason, an important processing step is to filter the high-resolution reference DEM to remove the high spatial frequency components higher than those that occur in contour-based DEM.

There are many methods that can be used to filter the high resolution DEM, such as 3x3 spatial domain filters and Gaussian smoothing. All are a compromise between obtaining sufficient suppression of high-spatial-frequency energy, and preferably little or no suppression of energy of low spatial frequencies (Fig. 3). Simple averaging operators (*N*x*N*) give poor filtering since they provide only a nominal suppression of high spatial frequencies; repeated applications of such filters achieve sufficient high-frequency suppression, but also suppress the required low-spatial-frequency data. A more productive approach is to design a low pass filter that is flat at low spatial frequencies, and exhibits a rapid fall-off in response above the spatial frequencies not represented in the DEM under test. Such filters preserve detail across the entire range of spatial frequencies represented within the DEM under test while largely suppressing data at all other spatial frequencies.

In the present case, a 127x127 circularly symmetric finite impulse response (FIR) filter was designed with a cut-off corresponding to a spatial scale of 25 m (Fig. 3), or 2/25 times the spatial frequency corresponding to the original 2-m resolution LIDAR-derived DEM data.

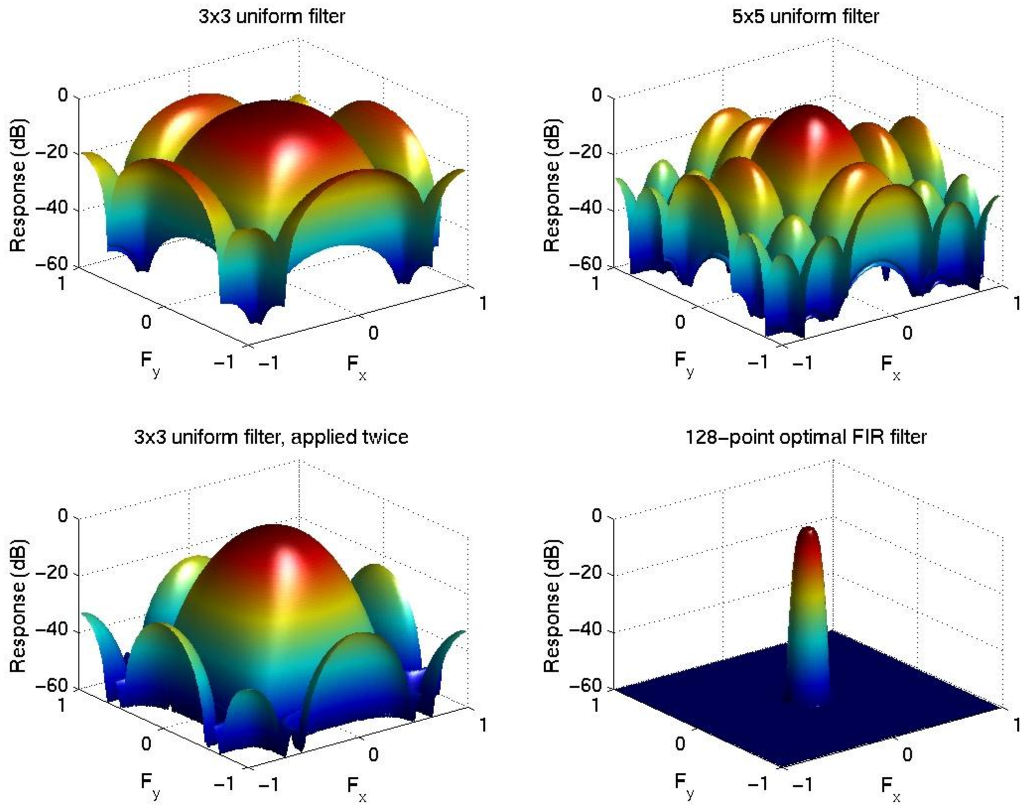



**Fig. 3** The filter at top left is a standard 3×3 low pass filter. The flattened and wide central peak indicates that this filter suppresses information at scales greater than 25 m while the smaller peripheral peaks indicate that the filter also leaks information at scales less than 25 m that should be suppressed. The standard 5x5 low pass filter at top right does not suppress quite so much information from the central (> 25 m) peak, but is extremely poor at filtering out high frequency signal from scales less than 25 m. Using the 3x3 filter twice does give a significant improvement. However, the finite impulse response filter used in this study (bottom right) is clearly superior in both retaining low frequency information while filtering out almost all the high frequency information.

The filter was designed using the frequency transformation of a one-dimensional FIR filter (Lim 1990), which itself is generated from a flat pass- and stop-band (0dB and –60dB respectively) filter, and an unconstrained transition region (Selesnick et al. 1995). Filtering of the 2-m LIDAR DEM in this way guarantees the generation of an accurate reference DEM with a flat response at all spatial frequencies up to a value corresponding to a scale of 25 m (Figs. 4 and 5).

### 3.3 Spatial estimates of DEM accuracy

As discussed previously, the derivation of global accuracy statistics such as RMS error are of limited value because they do not provide any information on the spatial variability of DEM accuracy. However, it is clearly not possible to have available a reference DEM for large areas. As a first step we decided to carry out terrain-based analysis of error to determine

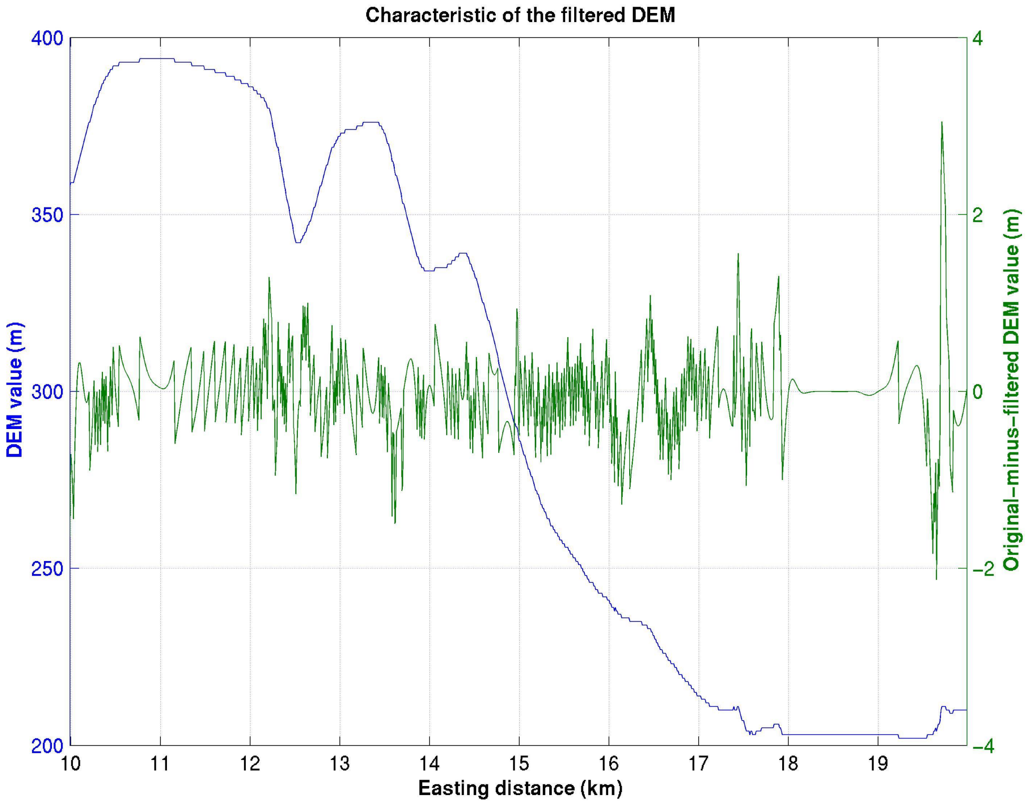



**Fig. 4.** The differences between the original and the filtered DEM are quite subtle, when viewed at a broad scale – although obviously the filtered version contains no energy at spatial frequencies above that corresponding to 25 m. This figure shows a slice through the original DEM (in blue), and the difference between the original and filtered DEM (in green). The original DEM is discretised to 16-bits, and the filtered DEM is floating point, so a significant part of the difference between the two DEMs can be related to quantisation noise. Notice, however, that changes in the difference over and above the ± 0.5 m difference can be seen where there are sharp changes in the DEM – these simply show the effect of the filtering operation.

whether we can predict spatial variability of RMS error for the small area of LIDAR data currently available. This involved selecting subsets of the DEM based on terrain attributes, and determining RMS error. This is the general approach used by Carlisle (2000), who developed 96 terrain parameter surfaces from which to build a regression model for RMS error variability. While this general approach seems to hold promise, the logistic demands of generating so many terrain-parameter surfaces in order to apply this type of model to the whole of New Zealand seems impracticable. As an alternative approach, we decided to determine the spatial variability of error in relation to landform classifications that either already exist, or could be simply derived from existing land classifications such as the New Zealand Land Resource Inventory (NZLRI – MWD 1974). This approach is based on the broad working hypothesis that DEM accuracy should vary with the density of contour and other topographic data available from which to derive the DEM, in relation to the complexity of the terrain being modelled. Assuming valid relationships can be derived that explain variation in spatial accuracy in relation to landform, we would then use these relationships to model to first-order elevation accuracy over the whole national DEM surface.

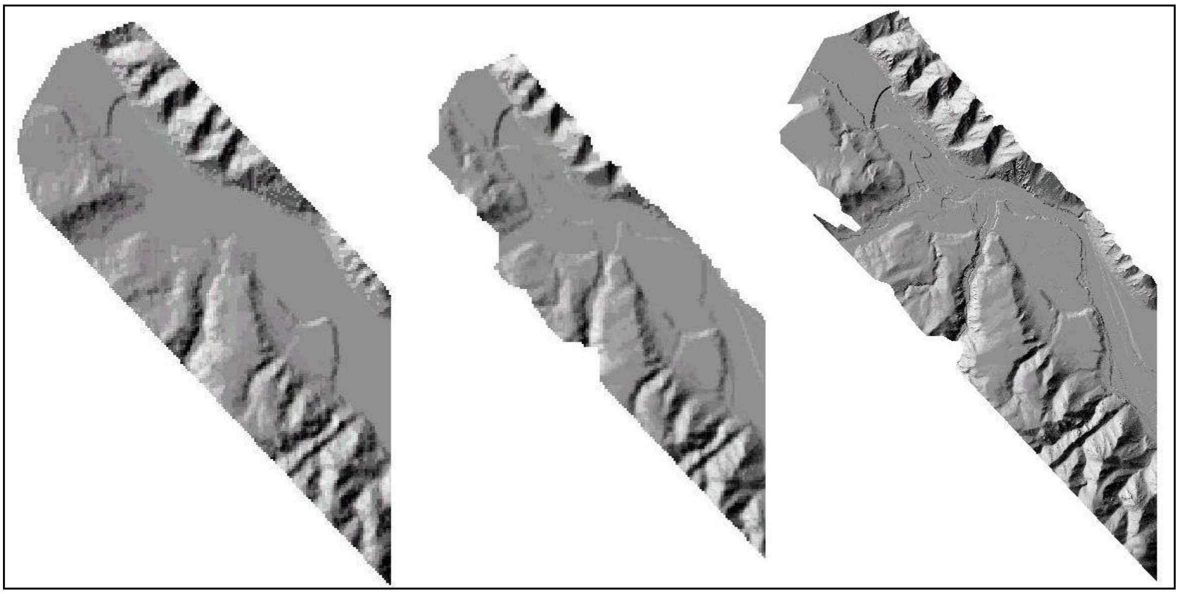


**Fig. 5** On the left is the original 25-m national DEM for our initial accuracy study area in the lower Waitaki from the Waitaki Hydro dam and Lake Waitaki at top left almost to Kurow. On the right is the original 2-m LIDAR reference data for the same area, and in between them is the filtered and resampled (to 25 m) reference DEM. Note that the filtered reference DEM covers a smaller area due the filtering process that cannot use cells within half of the filters width of the edge of the reference area.

# 4. Results

## 4.1 Global accuracy statistics

Using the raw and filtered LIDAR reference DEM to determine the vertical accuracy of the contour-based national DEM, we obtained the error statistics shown in Table 1. Note that the 'GPS' accuracy assessment is for a different area. The obvious differences between these global assessments of DEM accuracy are that the LIDAR analyses indicate a consistent bias to overestimating elevation in the national DEM (mean error >6 m), whereas the previous GPS-based analysis in another location indicated a much smaller bias (mean error <0.5 m). The RMS statistics are also higher for the LIDAR analyses, although the filtering of the LIDAR DEM to remove high-frequency data clearly improves RMS error at the spatial scale of the national DEM, and has an even more pronounced effect on standard deviation (SD) of error, which is almost halved after filtering. We also report the mean absolute error, but it does not seem to be as sensitive as the other statistics to filtering.

**Table 1** Accuracy statistics comparing the contour-based national DEM to the raw and filtered LIDAR reference DEM. For comparison, the results of a previous analysis comparing 2700 GPS points with the national DEM in another area are also shown.

| | Mean Error | Mean Absolute Error | RMS | SD |
|---|---|---|---|---|
| 1. Raw LIDAR | 6.24 | 7.27 | 11.91 | 10.14 |
| 2. Filtered LIDAR | 6.33 | 6.95 | 8.15 | 5.31 |
| 3. GPS | 0.41 | - | 6.15 | 6.13 |

## 4.2 Local accuracy statistics

The results of our analysis of the spatial accuracy of the national DEM in relation to both a detailed landform classification and the coarser NZLRI classification are illustrated in Figs. 6 and 7. These analyses clearly show that DEM accuracy is poorest in the river valley where the national DEM (based on 20-m contours) is limited by its ability to depict elevation variation within the resolution of the contours. Even after the filtering process has been used to remove high-frequency signal that the contour-based DEM could not be expected to show, there is still substantial error remaining. The lake, which is flat once filtered (i.e., no waves), has a very low SD, but RMS and mean error are close to the mean for the whole surface analysed. We do anticipate that these statistics may vary, depending upon how close the surface of the lake is to the elevation given for the lake shoreline in our topographic database. In this case the lake is a hydro-electrical storage lake with a surface height that may vary by several metres. Terraces display similar error statistics to the lake, although RMS and mean error may vary in relation to how closely the terrace surface elevation is to a contour interval. Landform classes with relief ranging from rolling to very steep terrain all display RMS error a little below the mean for the whole surface, but very close to the figure obtained previously by comparing a GPS survey with the contour-based DEM in another area of hill country. Error analysis using the less spatially detailed LRI landform classification shows a very similar pattern (Fig. 7) to the results found using the detailed landform classification.

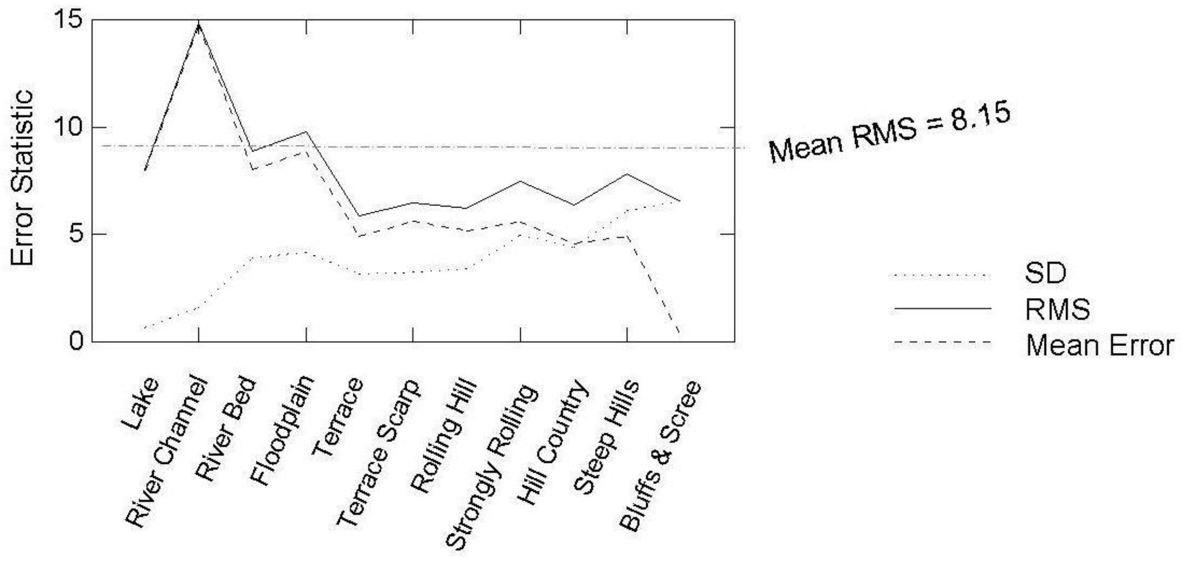



**Fig. 6** Spatial accuracy in relation to a detailed classification of landform type. This graph highlights the larger errors associated with river channel areas.

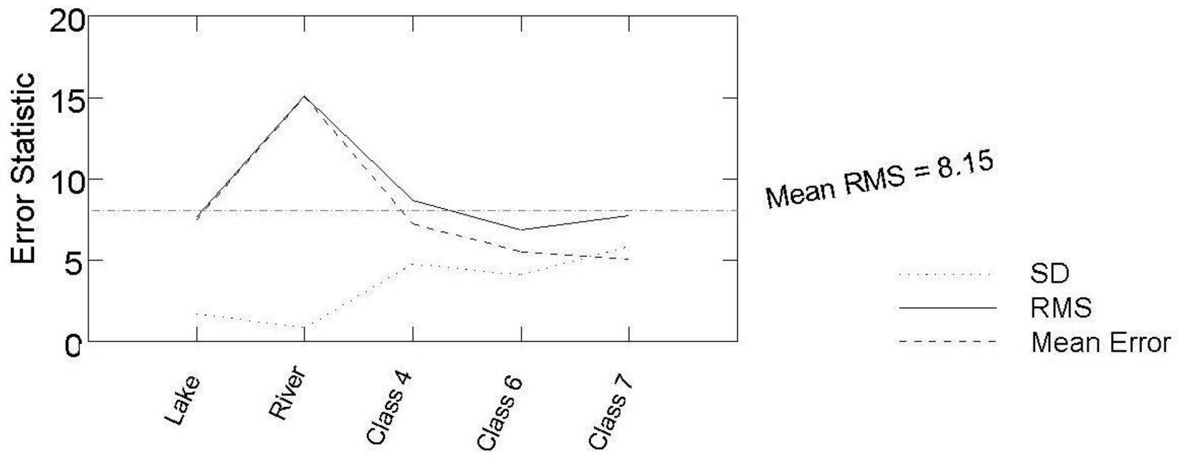



**Fig. 7** Spatial accuracy in relation to the NZLRI classification also highlights the larger errors associated with river channel areas, and the similarity of RMS in areas of moderate relief (class 4, 6 and 7 hill country).

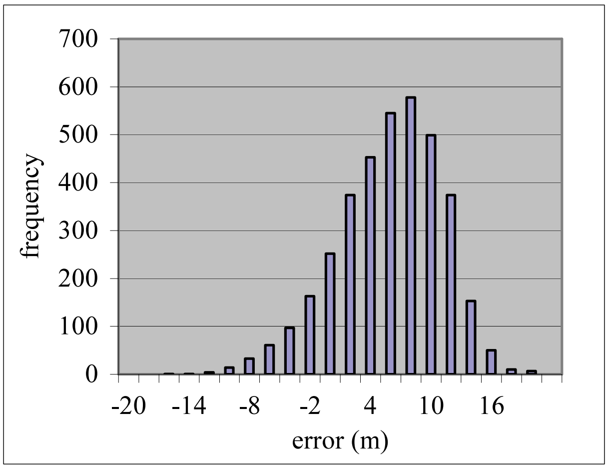
It is important to note that the earlier analysis of the national DEM against GPS data (Table 1) yielded a very low mean error and somewhat lower RMS value for the surface analysed, than has the current analysis using LIDAR. Certainly the mean error statistic shows the national DEM has a positive bias compared to the reference LIDAR dataset. The difference between the LIDAR and GPS figures for mean error is most likely to be related primarily to overestimation of elevations in the valley-floor. The 2700 GPS elevation points used in the previous analysis were a compilation of existing data collected for a variety of purposes, but which did not cover a full range of landform types. As a result the type of terrain that now appears to be a major source of error was not represented in the original survey and analysis.

There is in fact a plethora of different accuracy statistics that can be used to assess DEM accuracy. Much in the same way that there is no 'one right' interpolation algorithm, there is also no 'one right' statistic for describing DEM accuracy. Each has its place and purpose and it is perhaps more important to have tools that can easily be modified to calculate different statistics on demand (given the necessary algorithm) than it is to attempt to calculate a complete set of all accuracy statistics. Nonetheless, in Table 2 we attempt to show a range of widely used statistics from the more standard RMS and SD (already described) through to less commonly used statistics such as the accuracy ratio, which eliminates the effects of relative relief from measurement deviation (Wood 1996) and Moran's I, which measures spatial autocorrelation of error (Bailey & Gatrell 1995). Although not shown in Table 2, we calculated other error population statistics such as skewness and kurtosis. All these latter statistics have been gaining importance because of the use of Monte Carlo simulation techniques for assessing the potential of error propagation on spatial modelling results (e.g., Ehlschlaeger 2002).

**Table 2** Accuracy statistics comparing the contour-based national DEM to the raw and filtered LIDAR reference DEM. For comparison, the results of a previous analysis comparing 2700 GPS points with the national DEM in another area are also shown.

| | **RMSE** | **Mean abs. error** | **Mean error** | **Standard deviation** | **Maximum error** | **Minimum error** | **Accuracy ratio** | **Morans I** |
|---|---|---|---|---|---|---|---|---|
| Lake | 7.99 | 7.94 | 7.94 | 0.87 | 9.86 | -0.32 | 9.07 | 0.088 |
| Channel | 14.40 | 14.33 | 14.33 | 1.47 | 18.31 | 8.68 | 6.49 | 0.606 |
| Bed | 8.31 | 7.70 | 7.70 | 3.13 | 17.09 | -2.60 | 0.77 | 0.934 |
| Floodplain | 8.52 | 7.31 | 7.29 | 4.42 | 17.47 | -2.16 | 0.66 | 0.908 |
| Terraces | 5.57 | 4.87 | 4.62 | 3.11 | 15.16 | -8.81 | 0.22 | 0.767 |
| Scarp | 6.54 | 6.02 | 6.02 | 2.61 | 12.42 | 0.72 | 0.71 | 0.238 |
| Undulating | 6.25 | 5.60 | 5.45 | 3.06 | 16.05 | -7.86 | 0.11 | 0.722 |
| Rolling | 6.31 | 5.42 | 4.68 | 4.23 | 15.22 | -8.32 | 0.26 | 0.717 |
| Hilly | 7.37 | 6.36 | 5.83 | 4.51 | 17.41 | -7.20 | 0.15 | 0.772 |
| Steep | 7.13 | 6.07 | 4.90 | 5.18 | 19.85 | -16.26 | 0.11 | 0.837 |
| Bluff/Scree | 5.12 | 3.94 | 0.00 | 5.14 | 14.54 | -10.51 | 0.12 | 0.354 |
| | | | | | | | | |
| Global | 8.24 | 7.34 | 7.18 | 4.04 | 19.85 | -16.26 | 0.16 | 0.631 |

In order to give some indication of the spatial variability of uncertainty within the landscape zones identified above, we also looked briefly at the error distributions within several parts of the surface more closely. Figs. 8 and 9 show the error distributions within steep hill country and braided riverbed areas respectively. Interestingly these show that some of the assumptions for Monte Carlo simulations are not necessarily true of our data. For example, the data are somewhat skewed (i.e., are non-normal) and as a result do not have a zero mean error. Figs. 10 and 11 illustrate semi-variograms for the same data subsets. These graphs, like the Morans I statistic, provide information on spatial autocorrelation of error that can be useful in kriging and other geostatistical analyses.



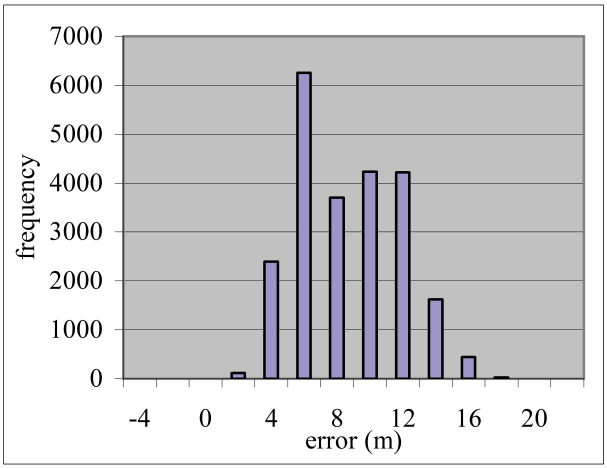
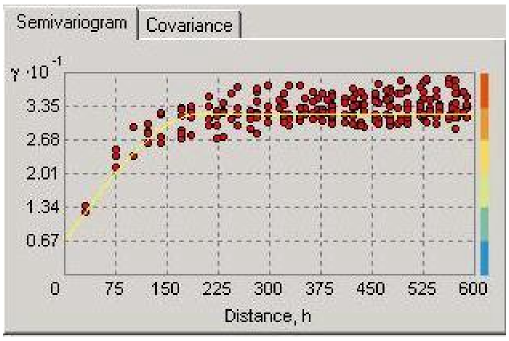




**Fig. 8** Histogram showing error frequency distribution for areas of steep hill country (n = 3669). Note that the distribution is negatively skewed with a mean error of 4.9 m.

**Fig. 9** Histogram showing error frequency distribution for areas of braided river bed (n = 23017). Distribution is near normal but with a mean of 7.7 m



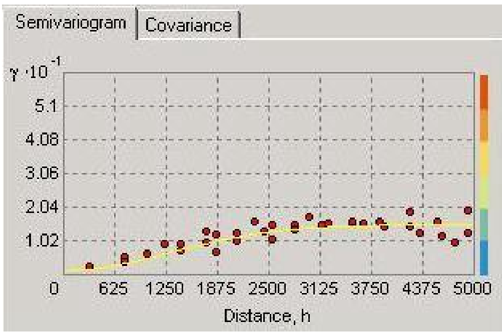




**Fig. 10** Semivariogram shows spatial auto-correlation of elevation errors for steep hill country areas. Major range for autocorrelation ***is 200 m.***

**Fig. 11** Semivariogram shows spatial auto-correlation of elevation errors for braided Riverbed. Major range for autocorrelation is ***3200 m***

These two plots are valuable in illustrating the distances over which areas are correlated for different landform types. However, they must also be interpreted with caution. Figure 10 shows that in steep hill country areas errors are correlated over a distance up to 200 m, whereas on the low-lying riverbed the major range for autocorrelation of errors is approximately 3.2 km. This seems a reasonable result given that we can assume that the filtering process described above has removed most of the autocorrelation of error that might occur at ranges below 25 m, and given the nature of the two types of terrain. However, Fig. 12 shows the actual errors mapped over the whole area. The reason for the 3.2 km range of spatial autocorrelation of error is clearly related to the ‘stepped valley’ error described earlier. Where the contours running along the valley side are closer to the cell being interpolated than the cross-valley contours, the interpolation algorithm tends to overestimate valley elevation. This effect is most pronounced at the mid-point between the cross-valley contours.

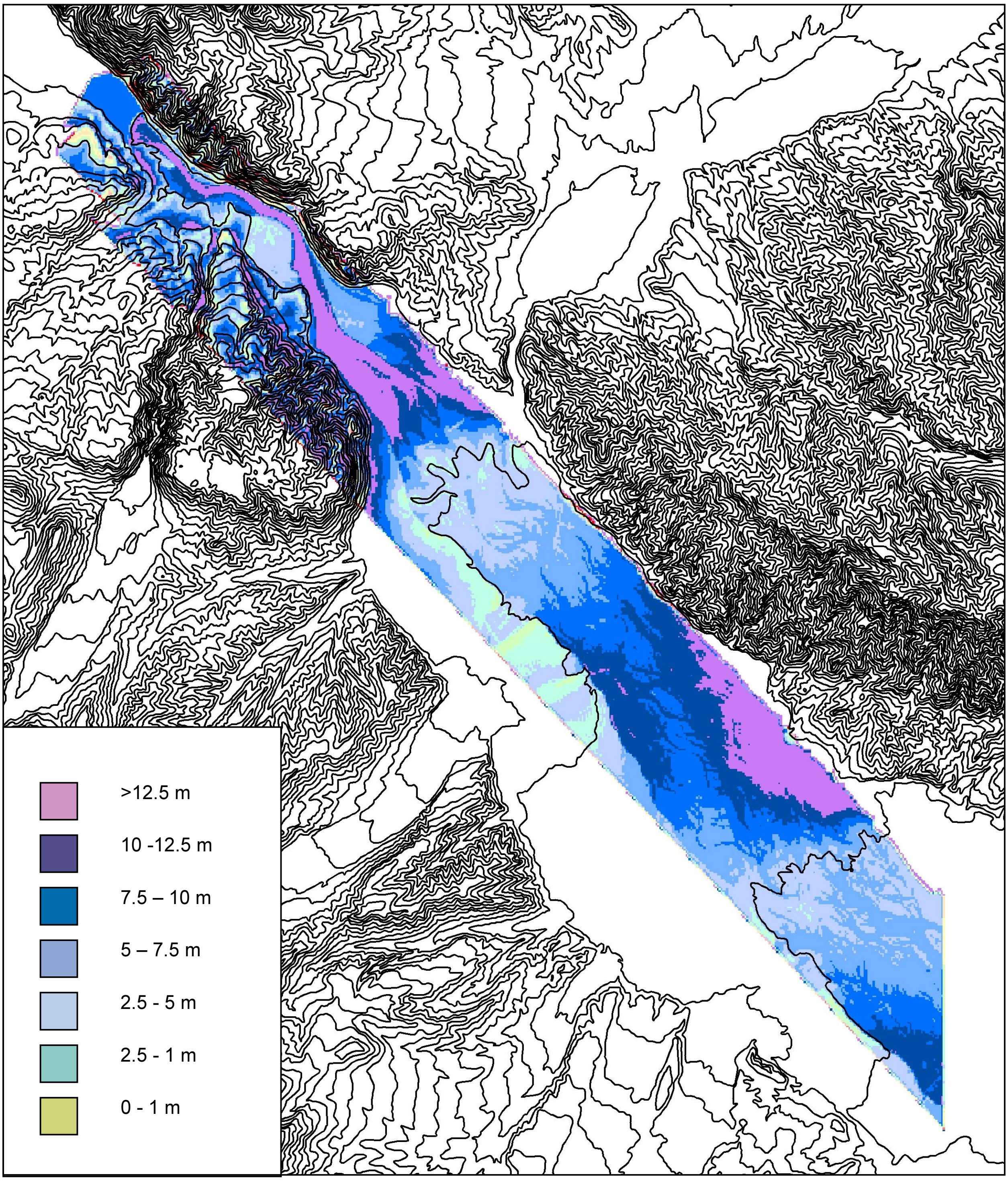



**Fig. 12** Error surface for the entire window of high-resolution LIDAR data. Note the overestimation of elevations in the incised river channel immediately below the hydro dam where the contour-based DEM contains insufficient information to separate the incised channel from its surroundings. Note also the increase in error with distance from cross-valley contours in the braided riverbed. This is caused by the contours running along the valley edge being closer to the point being interpolated and hence creating a 'stepped valley' effect. This is particularly noticeable at lower right where contours on the north bank cause a fan-like error structure to constrict the valley where in reality there are much flatter terrace landforms occurring.

## 5. Conclusions

We have used reference height data derived from aircraft laser altimetry, filtered to remove high-frequency data, to assess the accuracy of our 25-m-resolution, contour-based national DEM. The major errors in the national DEM, as measured by the reference LIDAR DEM, and ignoring the obvious problem of tree height in forests, are likely to be found at the local scale, chiefly as pockets of ill-fitting terrain data related to landform. While many analyses in the literature would typically quote RMS statistics, such global measures almost never detect pockets of ill-fitting data. A systematic comparison between the reference DEM and two qualitative classifications of landform indicate that while the spatial accuracy of the national DEM varies between landforms, areas of error are confined predominantly to valley floors, with much less spatial variation in error apparent for a range of other landforms analysed. Our results have implications when using the reference DEM for generating derived products, or when the DEM is included in other spatial models. Fundamentally, the analysis shows that global estimates of DEM error are of limited value, and that it is necessary to at least have landform-based error estimates, and preferably a detailed error surface.

Having analysed this small area of the national DEM comprehensively we ultimately hope to acquire sufficient LIDAR reference data to adequately sample a full range of landforms so that we can generate a comprehensive error surface for the DEM based on the distribution of landforms in the NZLRI or some other suitable landform classification. We also intend to test other DEMs generated by other organisations and/or using different software to compare and contrast accuracy and utility of DEMs for various applications.

## 6. Acknowledgements

This research was funded by the Foundation for Research, Science and Technology under contract C09X0015. The contour and other topographic data, from which the national DEM was generated, was supplied under licence by Land Information New Zealand (LINZ). The high resolution LIDAR data used in this study was kindly supplied by Meridian Energy.

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# 8. Appendices

**Appendix 1 Paper presented to Accuracy 2002 that formed the basis for this report.**

**Barringer, J.R.F.; McNeill, S.J.: Pairman, D. 2002:** Progress on assessing the accuracy of a high-resolution digital elevation model for New Zealand, *In* Hunter, G.: Lowell, K. *eds*., Proceedings of the 5$^{th}$ International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences, July 10-12, Melbourne Australia. Pp 187-195.

# PROGRESS ON ASSESSING THE ACCURACY OF A HIGH-RESOLUTION DIGITAL ELEVATION MODEL FOR NEW ZEALAND

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**Abstract**

By comparing contour-based digital elevation data with high-resolution LIDAR data we show that the accuracy of our contour-based national DEM is related to landform. Errors generally occur as irregular pockets of ill-fitting data mostly in river valleys (RMS $\approx$ 15 m). Accuracy did not vary in most other areas, with lakes, terraces, rolling, hilly and steep bluffs all having RMS in the order of 5-8 m. Advanced filtering techniques were used to remove high frequency data from the LIDAR reference DEM in order to render the comparison between the filtered LIDAR reference and national DEM valid.

**Keywords:** DEM, filtering, accuracy, landform, spatial variation

## 1. INTRODUCTION

The national coverage of high-resolution digital topographic data in New Zealand has recently become much more accessible because of changes in copyright policy by Land Information New Zealand (LINZ). As a result, a number of public and private organisations have developed regional or national digital elevation models (DEMs) at resolutions ranging down to 25 m. With modern GIS software and adequate computer hardware it is a straightforward process to develop high resolution DEMs using off-the-shelf tools. However, few of these large-area DEMs carry with them a clear indication of overall accuracy such as a root mean square error (RMS) statistic, let alone any comprehensive assessment of the spatial variability of DEM accuracy. Comprehensive measures of DEM accuracy can also be used to calculate the uncertainty of terrain parameters derived from the DEM, such as slope, aspect, and curvature, as well as providing the basic information for quantitative estimates of errors in drainage maps, shade maps, etc.

There are a number of important criteria that need to be met in order to provide an independent assessment of DEM accuracy (Wood, 1996). First, reference elevation data must be independent of the DEM generation process. Second, reference elevation data must be representative of the terrain. Third, if spatial estimates of accuracy are to be made, then they must be done within a framework of common spatial variability (i.e., with the same or similar spatial frequency characteristics). Unfortunately, while these criteria are easy to state, they are often difficult to satisfy. For example, a common strategy is to withhold certain data from the DEM generation process, and use the withheld data as ground truth (USGS, 1997). Withholding data degrades the accuracy of the DEM, and the most commonly used reference information (i.e., spot heights) may not provide a good sample of landscape positions to test DEM accuracy over a fully representative surface (Kumler, 1994). Furthermore, the input data also contain errors that are not always well described. For example LINZ state that their topographic data have a planimetric (x,y) accuracy with 90% of well-defined points within ±22 m; and a vertical (z) accuracy with 90% of well-defined points within ±5 m, and contour lines within ±10 m (LINZ, 2002). However, what constitutes a "well defined" point is not explained, so as a statement of data accuracy it is not useful when attempting to estimate the errors in, say, slope maps. In effect, DEM accuracy estimates derived using withheld input data as ground truth may only tell us how well we have converted our input data to DEM format, not how accurately the DEM represents the real land surface.

More recently some researchers have utilised the satellite global positioning system (GPS) to provide truly independent ground truth data with sub-metre data accuracies that are approximately an order of magnitude better than medium resolution photogrammetric data, and on a par with the accuracy of surveyed points (e.g., Barringer & Lilburne, 1997; Carlisle, 2000). However, like traditionally surveyed spot height data it is difficult to collect substantial amounts of ground truth data to properly test the accuracy of a DEM surface. GPS data has also been used in estimating spatial variability of DEM accuracy (Carlisle, 2000). Although when applied globally statistics such as RMS error are not particularly sensitive to localised DEM error, Carlisle developed regression models for creating an RMS surface using correlations with a variety of terrain parameters.

This paper describes the algorithm used to generate the national DEM, the process used to generate a high quality reference DEM from LIDAR data, and progress on developing detailed methods by which independent ground truth is used to test the accuracy of the national DEM over several distinct landform types.

## 2. BUILDING THE NATIONAL DEM

To generate a raster DEM from a vector set of contours, we must first define an interpolation process. The objective of such an interpolation is to define a height at each grid position in the raster image that best represents the surface defined by the contours. Unfortunately, the best surface representation is somewhat dependent on the intended use of the DEM. Therefore different interpolation methods may be preferable depending on the end use.

### 2.1 Interpolation method for Landcare Research 25 m DEM

Landcare Research has produced a national DEM at 25 m postings to be consistent with the 20-m contours and spot height information available from LINZ. The aim in producing this DEM has been absolute elevation correctness and speed of interpolation, rather than hydrological correctness, slope continuity, or some other performance goal.

For any regular and complete set of contours, any region will be bounded by contours of at most two different levels (Figure 1). The interpolator we have developed makes use of this contour topology by (without crossing contours) using a neighbourhood expansion process to grow into the regions bounded by contours while keeping track of the minimum distance to two different contour levels. Once the neighbourhood process has been completed, each pixel within the region will have the minimum distances to the bounding contours at two different levels (or one if bounded by a single contour elevation). The height assigned to the point is a ratio of these two levels in inverse proportion to the minimum distance found. This method ensures that both bounding contour levels affect the whole region bounded, even if no line can be drawn from a point to one of the bounding contour levels without crossing the other contour. Thus, valleys are not flattened out even when obscured from the lower contour (Figure 1).

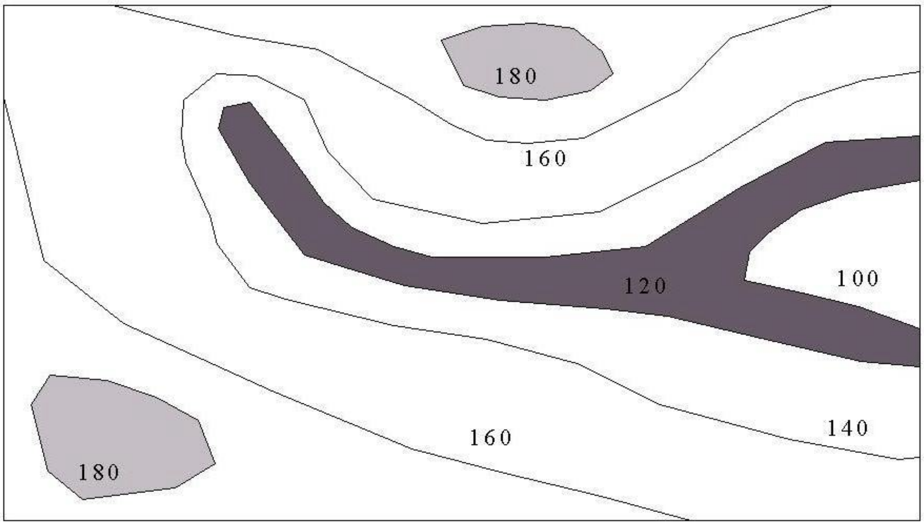


Figure 1. All areas are bounded by two contours apart from those in light grey, which are bounded by only one. The whole of the dark grey region is interpolated between 100 and 120 m, even the neck of the valley obscured from the 100-m contour.

Unfortunately the introduction of mid-slope spot heights and non-regular contours (e.g., lake shorelines), break the topology described above and introduces a third height adjacent to the area being interpolated. At present we still track the two minimum distances to the two nearest different defined heights. Artefacts in the surface can be found where the set of two nearest heights changes.

If a contour passes through a DEM pixel, then that pixel is set to the contour level. A contour is considered to have passed through the pixel if it enters the diamond connecting the mid-points of the pixel's four sides, or if it has a node within the pixel. If more than one contour passes through the pixel, then the level assigned is that of the contour passing closest to the pixel's centre. In this latter case, care is taken to interpolate from the contours nearest the pixel's boundaries, irrespective of which contour was used to assign the pixel value.

## 2.2 Interpolator implications

The interpolation method described above results in some undesirable DEM characteristics that users should be aware of:

1. Hilltops without a spot height will be flattened at the level of the highest contour, as the region within that contour only has a single adjacent elevation to interpolate from.
2. As mentioned above, artefacts can appear near mid-slope spot heights or contours, such as lake shorelines, which are not at the regular 20-m spacing. To alleviate this effect, we have excluded mid-slope spot heights when generating the DEM.
3. As pixels with contours passing through them are set to a contour value, there is an over-representation of pixels with a modulo-20-m elevation value. This is more noticeable where the contours are dense compared with the 25-m pixel spacing.
4. Slope continuity is not maintained across contours or spot heights.

While some of the above characteristics are not aesthetically pleasing, they are unlikely to have a great impact on the overall absolute accuracy of the DEM. The first two will only affect small areas within the DEM. Enforcing slope continuity or other constraints such as hydrological correctness can in fact reduce absolute accuracy.

### 2.3 Future improvements

We are currently developing a new version of the DEM interpolation algorithm with the following refinements:

1. Pixels will be interpolated between the two closest contours to its centre, even when one or more contours pass through the pixel.
2. The distances to the closest (different) contours will be tracked using real arithmetic in place of integer, and the path taken through a pixel will impact on the accumulated minimum distance.
3. The three closest (different) contours will be tracked allowing a smooth transition when the closest pair changes.
4. It may be possible to generate a set of pseudo spot heights to occupy the centre of closed contours representing hilltops without any spot height currently defined.

The first two of these improvements are most likely to have an impact on the absolute accuracy as they affect a larger number of pixels. The other two refinements, while reducing undesirable artefacts, are relatively limited in the area they will affect.

## 3. COMPARING THE REFERENCE DEM TO CONTOUR-BASED DEM

To determine the accuracy of the national DEM generated from contours using the method outlined earlier, height information is required that has a quality that is known to be at least as good as the DEM under test. Spot height information provides little information about the spatial characteristics of a DEM at a wide range of scales, since the spatial density of spot heights is not sufficiently great. We therefore chose to check the national DEM against a reference high-resolution DEM. Since the contour-derived national DEM represents the finest scale for which we have dense whole-country data, it is necessary to select higher-resolution DEMs of selected regions. Necessarily, this approach assumes that the higher-resolution DEM has characteristics that are indicative of more general regions in the landscape, rather than having characteristics that are unique to one region, for it would be difficult to generalise the results of the comparison if this were not the case.

As a first attempt at an accuracy assessment, we have chosen to use LIDAR data as the reference dataset, although the methods described here are applicable to all reference DEM sources. The LIDAR data used in this analysis were gathered as a series of *(x,y,z)*-points, with an average sample spacing of 2.5 m, and an approximate vertical accuracy of 0.25 m (Jonas, 2001). These LIDAR points were then made into a triangulated irregular network and rasterised to form a DEM with a spatial resolution of 2 m, in the same projection as the contour DEM.

### 3.1 Comparison methodology

Unless the reference DEM happens to have been gathered at exactly the same spatial scale as the contour-based DEM, one of the DEMs needs to be resampled to match the other. When the contour-based DEM is resampled to match the resolution of the reference DEM, a straightforward sample-by-sample comparison is not valid, since the high-resolution DEM contains information at high spatial frequencies that are not present in the lower-resolution contour-based DEM. It does not make sense to compare these two DEMs as-is, since the key task is *to estimate the accuracy of the contour DEM at the spatial scale at which it is generated*. For this reason, an important processing step is to filter the high-resolution reference DEM to remove the high spatial frequency components higher than those that occur in contour-based DEM.

There are many methods that can be used to filter the high resolution DEM, such as 3x3 spatial domain filters and Gaussian smoothing. All are a compromise between obtaining sufficient suppression of high-spatial-frequency energy, and preferably little or no suppression of energy of low spatial frequencies. Simple averaging operators (*N*x*N*) give poor filtering since they provide only a nominal suppression of high spatial frequencies; repeated applications of such filters achieve sufficient high-frequency suppression, but also suppress the required low-spatial-frequency data. A more productive approach is to design a low pass filter that is flat at low spatial frequencies, and exhibits a rapid fall-off in response above the spatial frequencies not represented in the DEM under test. Such filters preserve detail across the entire range of spatial frequencies represented within the DEM under test while largely suppressing data at all other spatial frequencies.

In the present case, a 127x127 circularly symmetric finite impulse response (FIR) filter was designed with a cut-off corresponding to a spatial scale of 25 m, or 2/25 times the spatial frequency corresponding to the original 2-m resolution LIDAR-derived DEM data. The filter was designed using the frequency transformation of a one-dimensional FIR filter (Lim, 1990), which itself is generated from a flat pass- and stop-band (0dB and –60dB respectively) filter, and an unconstrained transition region (Selesnick *et al.* 1995). Filtering of the 2-m LIDAR DEM in this way guarantees the generation of an accurate reference DEM with a flat response at all spatial frequencies up to a value corresponding to a scale of 25 m.

### 3.2 Spatial estimates of DEM accuracy

As discussed previously, the derivation of global accuracy statistics such as RMS error are of limited value because they do not provide any information on the spatial variability of DEM accuracy. However, it is clearly not possible to have available a reference DEM for large areas. As a first step we decided to carry out terrain-based analysis of error to determine whether we can predict spatial variability of RMS error for the small area of LIDAR data currently available. This involved selecting subsets of the DEM based on terrain attributes, and determining RMS error. This is the general approach used by Carlisle (2000), who developed 96 terrain parameter surfaces from which to build a regression model for RMS error variability. While this general approach seems to hold promise, the logistic demands of generating so many terrain parameter surfaces in order to apply this type of model to the whole of New Zealand seems impracticable. As an alternative approach, we decided to determine the error spatial variability in relation to landform classifications that either already exist, or could be simply derived from existing land classifications such as the New Zealand Land Resource Inventory (NZLRI – MWD, 1974). This approach is based on the broad working hypothesis that DEM accuracy should vary with the density of contour and other topographic data available from which to derive the DEM, in relation to the complexity of the terrain being modelled. Assuming valid relationships can be derived that explain variation in spatial accuracy in relation to landform, we would then use these relationships to model to first-order elevation accuracy over the whole national DEM surface.

# 4. RESULTS

Using the raw and filtered LIDAR reference DEM to determine the vertical accuracy of the contour-based national DEM, we obtained the error statistics shown in Table 1. Note that the "GPS" accuracy assessment is for a different area. The obvious differences between these global assessments of DEM accuracy are that the LIDAR analyses indicate a consistent bias to over-estimating elevation in the national DEM (mean error > 6 m), whereas the previous GPS-based analysis in another location indicated a much smaller bias (mean error < 0.5 m). The RMS statistics are also higher for the LIDAR analyses, although the filtering of the LIDAR DEM to remove high frequency data clearly improves RMS error at the spatial scale of the national DEM.

**Table 1.** Accuracy statistics comparing the contour-based national DEM to the raw and filtered LIDAR reference DEM. For comparison, the results of a previous analysis comparing 2700 GPS points with the national DEM in another area are also shown.

| | Mean Error | Mean Absolute Error | RMS | SD |
|---|---|---|---|---|
| 1. Raw LIDAR | 6.24 | 7.27 | 11.91 | 10.14 |
| 2. Filtered LIDAR | 6.33 | 6.95 | 8.15 | 5.31 |
| 3. GPS | 0.41 | - | 6.15 | 6.13 |

The results of our analysis of the spatial accuracy of the national DEM in relation to both a detailed landform classification and the coarser NZLRI classification are illustrated in Figures 2–3. These analyses clearly show that DEM accuracy is poorest in the river valley where the national DEM (based on 20 m contours) is limited by its ability to depict elevation variation within the resolution of the contours. Even after the filtering process has been used to remove high frequency signal that the contour-based DEM could not be expected to show, there is still substantial error remaining. The lake, which is flat once filtered (i.e., no waves), has a very low SD, but RMS and mean error are close to the mean for the whole surface analysed. We do anticipate that these statistics may vary, depending upon how close the surface of the lake is to the elevation given to the lake shoreline in our topographic database. In this case the lake is a hydro electrical storage lake with a surface height that may vary by several metres. Terraces display similar error statistics to the lake, although RMS and mean error may vary in relation to how closely the terrace surface elevation is to a contour interval. Landform classes with relief ranging from rolling to very steep terrain all display RMS error a little below the mean for the whole surface, but very close to the figure obtained previously by comparing a GPS survey with the contour-based DEM in another area of hill country. Error analysis using the less spatially detailed LRI landform classification shows a very similar pattern (Figure 3) to the results found using the detailed landform classification.

It is important to note that the earlier analysis of the national DEM against GPS data (Table 1) yielded a very low mean error and somewhat lower RMS value for the surface analysed, than has the current analysis using LIDAR. Certainly the mean error statistic shows the national DEM has a positive bias compared to the reference LIDAR dataset. The difference between the LIDAR and GPS figures for mean error is most likely to be related primarily to over-estimation of elevations in the valley-floor. The 2700 GPS elevation points used in the previous analysis were a compilation of existing data collected for a variety of purposes, but which did not cover a full range of landform types. As a result the type of terrain that now appears to be a major source of error was not represented in the original survey and analysis.

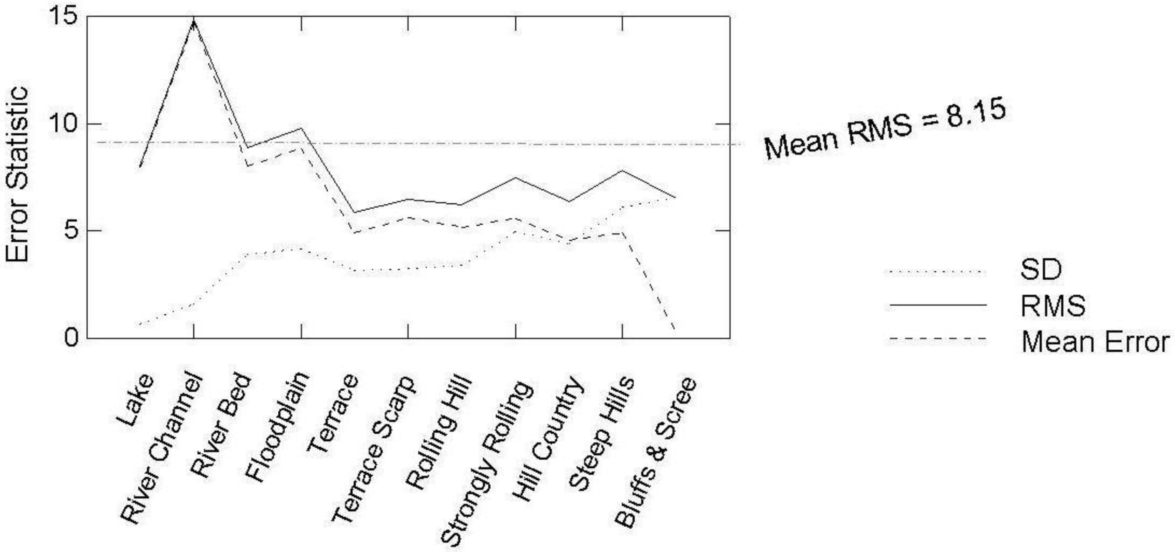


**Figure 2.** Spatial accuracy in relation to a detailed classification of landform type. This graph highlights the larger errors associated with river channel areas.

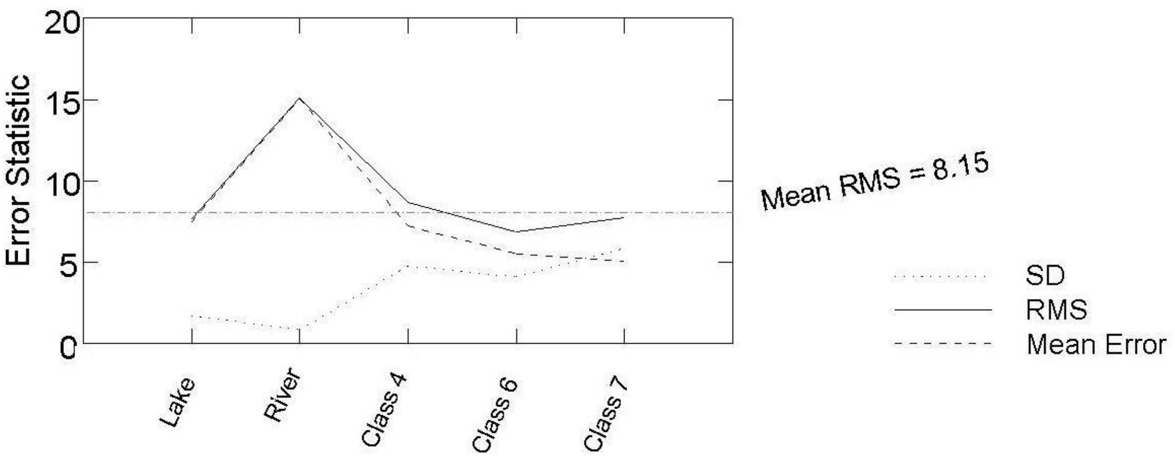


**Figure 3.** Spatial accuracy in relation to the NZLRI classification also highlights the larger errors associated with river channel areas, and the similarity of RMS in areas of moderate relief (class 4, 6 and 7 hill country).

## 5. CONCLUSIONS

We have used reference height data derived from aircraft laser altimetry, filtered to remove high frequency data, to assess the accuracy of our 25-m-resolution, contour-based national DEM. The major errors in the national DEM, as measured by the reference LIDAR DEM, and ignoring the obvious problem of tree height in forests, are likely to be found at the local scale, chiefly as pockets of ill-fitting terrain data related to landform. While many analyses in the literature would typically quote RMS statistics, such global measures almost never detect pockets of ill-fitting data. A systematic comparison between the reference DEM and two qualitative classifications of landform indicate that while the spatial accuracy of the national DEM varies between landforms, areas of error are confined predominantly to valley floors, with little spatial variation in error apparent for a range of other landforms analysed. Our results have implications when using the reference DEM for generating derived products, or when the DEM is included in other spatial models. Fundamentally, the analysis shows that global estimates of DEM error are of limited value, and that it is necessary to at least have landform-based error estimates, and preferably a detailed error surface.

Having analysed this small area of the national DEM comprehensively we plan to extend this analysis to adjacent areas for which we also have LIDAR reference data available. Ultimately we hope to acquire sufficient LIDAR reference data to adequately sample a full range of landforms so that we can generate a comprehensive error surface for the DEM based on the distribution of landforms in the NZLRI or some other suitable landform classification. We also intend to test other DEMs generated by other organisations and/or using different software to compare and contrast accuracy and utility of DEMs for various applications.

**Acknowledgements**

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