Title: A practical method for creating a digital topographic surface for ecological plots using ground-based measurements

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SHORT COMMUNICATION for *Landscape Ecology*

Abstract

1) Context: Digital elevation models (DEM) are widely used in landscape ecology to link topographic features with biotic and abiotic factors. However, to date, high-resolution, affordable, and easy to process elevation data are not available for many study regions.

2) Objectives: Here we propose a field-based method for efficiently and inexpensively collecting or analysing already existing slope data. We compare the field approach to two commonly used remote sensing techniques to test the similarly of the DEMs using different methods.

3) Methods: To provide an ecological example of the method, we selected four 1-hectare forest plots and compared the DEM generated by using our field method with those derived from: i) coarse (~30m pixel) data from the Shuttle Radar Topography Mission (SRTM) and ii) high-resolution (~1m) data from Light Detection and Ranging devices (LiDAR).

4) Results: Field- and LiDAR-based DEMs showed strong concordance in two of the four sites. The sites where field-based and LiDAR DEMs substantially differed, suffered from relatively few LiDAR sampling points. Diagnostic tests suggested that the field-LiDAR discrepancy was due to dense over-storey vegetation, which reduced LiDAR's accuracy due to a failure to penetrate the forest canopy adequately in some areas.

5) Conclusions: Our method has the advantage of being quick and cheap to collect yet able to produce small-scale (plot-scale) DEMs of high quality. By using the R-code we have provided, ecologists will be able to use slope data (collected using any means) to generate a DEM without the need of specific skills in spatial sciences.

Keywords

Digital elevation models; DEM; topography; plots; algorithm; remote sensing; slope; LiDAR; SRTM; forests.

Introduction

Digital elevation models (DEMs) are used to represent topographic attributes of the Earth's surface, with a wide variety of practical applications (e.g., in agriculture, engineering, ecology, and telecommunications). They are also indispensable for quantifying environmental threats such as ground instability, erosion and vulnerability of surface features. With improvements in instrumentation, resolution, and the accuracy of remote-sensed data in measuring surface features, DEMs have become ubiquitous in environmental spatial analysis

(Ziadat 2007), with particular relevance to the questions of landscape ecology. Technically, a DEM (and the related digital terrain surface) is a numerical data file that embeds information on topography over a specified area, typically represented by a height map, and is often represented visually as a flattened two-dimensional surface (Erdogan 2009; Hu 1995). DEMs can be generated using many different methods, including photogrammetry, satellite-based imagery, digitisation of existing topographic maps, and field surveying. Each method has its advantages and caveats, and since many scientific studies and applications rely on DEMs, the consideration of data-acquisition costs, quality and accuracy, is crucial.

Many studies have examined factors that influence the quality-feasibility trade-off of DEM construction. Erdogan (2009) proposed three general classes, based on: a) accuracy, density and distribution of the source data; b) the interpolation process (i.e., algorithms); and c) characteristics of the generated surface (represented as uncertainty) (see also Fisher and Tate 2006). Two important influences on the accuracy of the source data of a DEM are sampling density and collection technique. Generally, the most accurate DEMs are produced with precise, highly sampled terrain data (Gong et al. 2000; Liu et al. 2007). In situations where terrain is complex and/or measured at a coarse resolution, the discrepancy between the DEM and the 'real-world' can be high (Gao 1997; Warren et al. 2004). Field surveying methods can yield high-resolution terrain data, but can be time consuming and labour intensive to collect. Alternatively, satellite- or aircraft-based techniques (e.g., Light Detection and Ranging: LiDAR) offer higher-density data capture, but are often limited in availability, expensive to purchase, and can suffer from occlusion of the ground-surface signal in vegetated areas such as forests (Su and Bork 2006).

In landscape ecology, DEMs are most often used to explore the relationship between slope/elevation and various biotic or abiotic variables. These might include forest structure and spatial patterns of individuals or species, fire severity and its behaviour, water and nutrient fluxes, soil properties and solar radiation (e.g., Lassueur et al. 2006; Linn et al. 2010; Seibert et al. 2007; Yin and Wang 1999). Many databases now exist for which slope data are available for mapping terrain at coarse scales (e.g., the Shuttle Radar Topography Mission [SRTM] global DEM), with an effective resolution of approximately 30 metres at the equator; see https://earthexplorer.usgs.gov). This product represents a remarkable achievement in the field of remote sensing, but its resolution might still be too coarse, depending on type and scale of the study. When that is the case, the remaining alternatives are either expensive and require specific skills (e.g., LiDAR), or easy to gather but complex to process (e.g., field data). If you choose to collect your own data in the field, what method do you use to interpolate these measurements? To date, a practical method for developing a DEM statistically, based on open-source software (e.g., Program R, Python), is not available. Such a method would streamline the field data interpolation process and enable field ecologists not familiar with computer software to generate DEMs and DEM plots.

Here we present a simple, practical and accurate method to create a high-resolution DEM, using field-collected data. In this short communication, we describe: i) the field-collection method, ii) the analysis algorithm, implemented as an R script, and iii) a working example of how our method compares with two commonly used data sources and methods in the forest ecology literature: the satellite-derived SRTM and local airborne LiDAR.

Methods

Plot design

Relative slope-angle data was collected from one-hectare plots within the Australia-wide tall-eucalypt AusPlots forest network, laid out on a grid of twenty-five 20 × 20 m subplots (see Wood et al. 2015 for details on plot choice, location, establishment and other measurements). For this study, we examined four of the 14 plots located within Tasmania (southern Australia); these were selected because slope information for all three DEM methods: SRTM, LiDAR and field-based, was available. Henceforth these sites are referred to according to their geographic location: "North Styx," "Weld River," "Bird Track," and "Mt. Field". To ensure the applicability of this method under different conditions, we included sites characterised by dense understorey (e.g., Weld River).

Relative slope data collection

The protocol for on-ground measurement of relative slope, operationally defined as the difference in relative elevation (vertical differences) between the observer and a target point, was designed to balance accuracy of measurement with time-efficient implementation. Measuring each subplot (marked out by four stake-posts) required two people (hereafter P1 and P2), as indicated in Fig. 1. Relative slope angles were estimated using a vertex hypsometer; a clinometer would also be suitable. The procedure is described diagrammatically in Fig. 1, for a 20-m subplot. The relative slopes were measured by P2, by aiming the cross-hair of the vertex towards an eye-height point on P1 (or a pre-established point on P1 equivalent to the eye level of P2, if P1 and P2 do not share the same height), and recording the angle (in ±degrees). If dense vegetation obscured the line of sight when standing, both people either crouched or sat (to maintain equivalent level). For 25 subplots, this yielded 100 raw relative slope measurements.

Data analysis – topographic map

Since the dimensions of the subplots were known, the relative slope heights were calculated via trigonometry (opposite side was based on the observed angle and adjacent side length). Individual subplot heights were converted to a common offset by propagating heights sequentially across each row/column and averaging. The heights of the mid-points of the subplot sides were inferred as the average of the relevant corner post heights measured from adjacent subplots (four values; two for plot edges). Similarly, the centre height was deduced from information on the four corner posts, and the centre-to-corner mid-points as the average height of the two subplot-edge mid-points. This yielded a 9 × 9 raster grid for each subplot.

Once this raster-based digital terrain surface was created, the average or steepest gradients and heterogeneity in heights across the plot were estimated. The raster was also smoothed (using `image.plots` and `filled.contour` functions in R). It was then converted to a digital elevation model by adding an offset (in metres above sea level) to each point, which is equal to the elevation of the plot derived from a GPS coordinate taken at a known point on the plot and then geo-referenced back to a global DEM such as SRTM.

Sample .CSV data files containing measurements of slopes at four 1-ha plots in Tasmania, are provided in the Supplementary Information. We also supply commented R code, which can be used to execute all the calculations summarized above. This code is customizable; it can produce raster grids at different resolutions, defined by varying the distance between measurements (subplots in our example), and create digital terrain surface maps and contour plots. The 'field' plot maps shown in Figure 2 and the Supplementary Figure 1 are generated with this open-source code, which may be freely distributed and modified (with attribution).

The final DEM for each site was created using the inverse distance-weighted (IDW) interpolation tool in ESRI ArcMap 10.4. We assessed the similarity of DEMs generated through the field-based method (10m resolution) with those obtained, for the same locations, using other common remote sensing techniques. DEMs were compared with models obtained from two alternative sources: 1-arcsecond (~ 30-m) SRTM (provided, for our study region, by Geoscience Australia: http://www.ga.gov.au/elvis), and a 1-m DEM created by triangulating points classified as 'ground' from airborne LiDAR data, supplied by the Department of Primary Industries, Parks, Water and Environment (DPIPWE) of Tasmania.

Statistical analyses

For each of the four study sites, 100 sample points, taken at 10-m intervals were generated (plus a central reference marker). Each of these points were associated to the elevation value extracted from the SRTM, LiDAR and field-based DEMs. Relative elevation was then calculated as the difference in elevation between each sample point and the reference point. We used two methods to compare values derived from alternative DEM sources: i) simple statistical metrics (absolute mean, minimum, and maximum) of differences between pairs of observations (SRTM-LiDAR, SRTM-field method, and LiDAR-field method), and ii) root mean square error (RMSE) for the three pairs of observations.

As a further test of similarity between DEMs, the Pearson correlation coefficient (r) between datasets was assessed, based on the subset of 25 random sample points for each site. This sampling procedure was then repeated (with replacement) 1,000 times to obtain the frequency distribution. All analyses were done using Program R v3.3.3 (R Core Team 2013).

Results

The number of LiDAR ground points available to generate the DEM varied between sites, with a maximum of 8,014 points for Mt Field and a minimum of 845 points for Weld River (Fig. 3). Graphic representation of ground point density for each site are included in Supplementary Material Fig. 2.

The minimum difference in relative elevation between methods (SRTM, LiDAR, and field-based) was small across all sites, while maximum and mean difference varied greatly depending on the pair of methods compared and the site (Table 1). In the two sites with the highest LiDAR ground-point density—Mt Field and North Styx—LiDAR and field-based observations were strongly concordant, displaying the lowest minimum and maximum difference, while the SRTM data showed the greatest differences due to its coarse resolution (Table 1; Fig. 4). In Bird Track, all pairs of comparison displayed similar values, whereas in Weld River the LiDAR data differed greatly from both SRTM and field-based data. Consequently, in both Mt Field and North Styx the lowest RMSE values were associated with the comparison between LiDAR and field based data. In Bird Track, by contrast, the SRTM-field method comparison had the lowest RMSE values, while in Weld River this was the case for the SRTM-LiDAR contrast.

Analyses of correlation-coefficient distribution agreed with the other statistical summaries. As expected, the relative elevation from LiDAR and SRTM showed only moderate correlation: mean *r* values were between 0.8 and 1.0 in Mt Field and North Styx, while they ranged between 0.7 and 1.0 in Bird Track and between 0.3 and 0.8 in Weld River. The relative elevation derived from our field method were more strongly correlated with LiDAR-derived than SRTM-derived data in all sites but Weld River. When comparing LiDAR with field method, mean *r* values ranged between 0.9 and 1.0 in Mt Field and North Styx (Fig. 5) and between 0.8 and 1.0 in Bird Track. Mean correlation between SRTM and field method was comparatively lower, ranging between 0.7 and 1.0 in Mt Field and North Styx and between 0.8 and 1.0 in Bird Track. In Weld River field observations were loosely correlated with LiDAR data; mean *r* values ranged from 0.0 to 0.8. Conversely, when comparing field method and SRTM, mean *r* values ranged between 0.4 and 1.0. Figures of the frequency distribution of *r* for each pair of comparisons can be found in Supplementary Material S2.

Interactive 3D renderings of the DEMs generated for each site are in Supplementary Material 3, presented as a visual representation of the differences between DEMs obtained using SRTM, LiDAR, and the field-method proposed in this study.

Discussion

We have presented an easy-to-use framework for creation of digital terrain surfaces and DEMs, and outlined how to collect field data in a systematic way to best serve this purpose. In addition, we provide the operational R script and functions for straightforward implementation. This provides a valuable toolkit for field ecologists who seek a means of rapid assessment of landscape features in areas where high-resolution remote-sensed data is unavailable. We demonstrated, using a selection of four 1-hectare forest plots, that the DEMs produced using our method are in strong accordance with those derived from high-quality remote-sensed imagery, and indeed superior in situations of uneven sampling density. Tools for implementation of DEMs into graphical displays, which are simple to interpret and use in subsequent analyses in landscape ecology, are also provided. Such methods can be modified and applied to any DEM derived dataset (irrespective of the data source).

Previous studies have demonstrated that the accuracy of DEMs is strongly influenced by a site's topographic variability and accessibility, as well as methodological issues such as point density, interpolation methods and spatial resolution of raw data (Bader and Ruijten 2008; Franklin 2001; Mitchard et al. 2012). Indeed, even once these data are collected there are inherent caveats and challenges when translating this information into a DEM using different frameworks (Guo et al. 2010), as summarised in Table 1. There have been many studies done comparing the use of LiDAR, SRTM and field-based generation of DEMs in ecology (e.g., Schumann et al. 2008; Zellweger et al. 2014). All point to the conclusion that field-based data collection will, in many practical circumstances, out-perform remote-sensed techniques—most appropriately where sufficient man power and time is available, permitting the modelling of finer topographic variation. Unlike other ground-based methods, such as differential levelling – which requires specific expertise as well as bulky, expensive and specialized surveying equipment, the method we have proposed is highly cost-effective and is straightforward to collect and apply, both in terms of field measurements and data processing. By comparison, LiDAR-derived DEMs, whilst powerful, can be expensive to obtain, complex to process with interpolation algorithms, and are not free from error (Erdogan 2009). Further, the generation of DEMs from point-cloud datasets requires specific expertise, particularly when raw data have not been classified on-ground (Liu 2008).

The methods that were used to collect the slope-angle data for the 1-hectare forest plots took two people less than half-a-day per site. Additionally, these on-ground data have high contiguous point density (we used 100 measurements per hectare) and were regularly spaced, resulting in a DEM that is insensitive to the choice of interpolation algorithm (Fig 3; SI Fig

2). Other advantages of on-ground measurements are that they allow researchers to become intimately familiar with their field sites/ plots (providing a useful ‘sanity check’ of the final map), and it encourages a standardised protocol. The obvious caveats are the requirement of two people to collect the data, and that in some locations it can be challenging to access the site of interest (e.g., in complex terrain, and densely vegetated or remote areas). It is also not suitable for surveying large landscapes. By contrast, LiDAR and photogrammetric methods can, if resources permit, be readily applied over a wide range of spatial scales while providing good spatial coverage at high resolution with relatively little need for field time (James et al. 2006). Therefore, the best survey method is one that is most well-suited to the terrain complexity.

The importance of spatial resolution of DEMs is well-studied in landscape ecology, particularly when modelling stream flows (e.g., Dixon and Earls 2009), soil processes (e.g., erosion and runoff) and forest health (e.g., canopy cover, anthropogenic disturbance such as logging; Coops et al. 2004; Trumbore et al. 2015). Results from such research indicate that the accuracy of slope data, as well as the mean and variance of slope values, decreases with lower DEM resolutions (Chang and Tsai 1991). Most often, slopes estimated from coarse-resolution data (e.g., 90 m pixels) can produce significant underestimates of true slopes (Zhang et al. 1999). The results from this study show how elevation data, obtained using a field method, can closely resemble those acquired with high-resolution techniques, such as LiDAR, in all cases except where the LiDAR survey produced an inadequate number of ground points.

Of the four evaluation sites, the LiDAR-derived DEM for Weld River was found to differ substantially from both SRTM and field-based methods (Table 1; Fig 4). This underscores the importance of having a high and consistent density of ground points for generating accurate DEMs. In fact, LiDAR point density was almost an order of magnitude lower in Weld than in any other site (i.e., 845 points/hectare for Weld; 8,014 points/hectare for Mt Field), possibly affecting DEM accuracy. The main factor that influences the realised number of ground points generated by a LiDAR survey is the thickness and structure of the vegetation, and the steepness of the slope (Su and Bork 2006). Supporting this inference, it has been shown repeatedly that LiDAR accuracy decreases with increasing topographic relief and canopy density (i.e., fewer ground-points with tall and obscuring over-story; Hodgson and Bresnahan 2004). There were also substantial and systematic differences between SRTM and the other two methods (LiDAR and field-based). This was not only due to the differences in resolution (i.e., SRTM 30m), but also to the intrinsic nature of SRTM imagery. The interferometric synthetic aperture radar (InSAR) used to generate the SRTM data products work by detecting electromagnetic energy in the microwave spectrum (~5.6cm; www.usgs.gov). As radar wavelengths do not penetrate rough surfaces, including the canopy, SRTM products would closely resemble the terrain only on bare ground or grasslands (Farr et al. 2007). Although vegetation-corrected SRTM DEMs have been generated, they are based on spatial products ranging in resolution from 3 arc-seconds (~90 m) to 30 arc-seconds (~1 km) (O'Loughlin et al. 2016). This does not allow for high-resolution spatial analyses needed for most ecological studies, and is incapable of capturing variations in micro-topography. In our plot-based examples, a major advantage of on-ground methods is that the measurements maintain accuracy irrespective of vegetation type, thickness or number of strata.

Landscape ecology is burgeoning with uses for high-quality DEMs, and there are many potential applications of easy-to-implement methods, such as the one we present here. Some examples of current and future applications for a DEM include: i) exploring the influence of slope on treefall and forest structure (Buettel et al. 2017), ii) microtopography, compared for multiple sites across a landscape, as a link between hydrology, soil stability and species richness/diversity (e.g., Moser et al. 2007), and iii) microtopography as a tool to investigate the influence of human and natural disturbances on local forest structure (e.g., Ehrenfeld 1995; Linn et al. 2010; Wood et al. 2011).

There are many innovations involved in the use of DEMs in ecology, and it seems inevitable that ongoing technological advances will reduce costs, improve data quality (James et al. 2006), and enhance the role of LiDAR and photogrammetry in the future. For example, ‘remote-sensed’ (but on-ground) data might become readily crowd sourced (e.g., via smartphone apps), greatly increasing data coverage and reducing costs to the researcher. Furthermore, ground-based methods of collecting high-resolution topographic data are also improving in the form of using robotised total stations (electronic theodolites able to automatically recognise a target, without the need to accurately sight it), differential GPS (improved GPS with accuracy of ~10 cm), and Zebedee, portable hand-held devices equipped with a 3D sensor (Bosse et al. 2012; James et al. 2006). Indeed, Brasington et al. (2003) reported on their ability to collect up to 3000 observations per day in the field and the technology has since improved. All of these envisaged technological methods may provide a more rapid, precise and accessible alternative to field-based data collection for future research. However, it is unclear when such methods will be widely available, and at what cost. A practical, low-cost method like that presented in this paper can yield a simple, high-resolution alternative that is available now. In making use of easily collectable field-based slope data, it allows for rapid construction of a DEM suitable for tackling a wide range of problems that might confront researchers in landscape ecology.

Table 1. Summary statistics for the four sites. Minimum, maximum, and mean (± standard error) of the difference (expressed as absolute value) between values obtained from SRTM, LiDAR and the field-based method; Root Mean Square Errors (RMSE) are also presented for each site. Values are expressed in metres. The number of LiDAR ground points available for each site is also reported.

		Bird Track	Mt Field	North Styx	Weld River
SRTM-LiDAR	Min	0.05	0.16	0.08	0.13
	Max	11.81	6.69	16.05	11.99
	Mean ± SE	3.02 (± 0.23)	2.33 (± 0.15)	5.10 (± 0.39)	4.35 (± 0.29)
	RMSE	3.82	2.79	6.39	5.21
SRTM-Field	Min	0.00	0.00	0.03	0.00
	Max	10.32	8.51	14.94	14.12
	Mean ± SE	3.15 (± 0.21)	2.73 (± 0.20)	5.94 (± 0.37)	3.75 (± 0.33)
	RMSE	3.77	3.35	6.97	4.96
LiDAR-Field	Min	0.09	0.00	0.01	0.27
	Max	10.72	3.28	5.43	15.03
	Mean ± SE	3.10 (± 0.24)	1.36 (± 0.09)	1.44 (± 0.11)	6.73 (± 0.35)
	RMSE	3.94	1.61	1.82	7.57
N. of LiDAR ground points		2,527	8,014	4,620	845

Figure captions

Note: for high resolution figures, see submitted PDFs.

Fig. 1 Methodology to (a-b) determine the centre of the subplot and (c) record slope angle from the centre to each post (post '0, 0' is shown in the example). Measures refer to the extent of the subplots used in the survey (20 × 20 m subplots laid out on a 1 ha grid).

Fig 2 Example of an R-script-generated raster grid. Contours are imposed using the `image.plot` and `contour` functions of the **`fields`** package. The colours indicate pixel height (in meters), from green (low) to yellow, orange and white (increasing height).

Fig. 3 LiDAR return points classified as 'ground' in the Weld River region, southern Tasmania. The density of ground points in the one-hectare forest plot (square box) is sparse relative to much of the surrounding area, and is the lowest recorded amongst the four sites.

Fig. 4 Two-dimensional contour plots of the digital elevation models of the four surveyed plots, obtained using data from (in order of theoretical increasing resolution): (i) the Shuttle Radar Topography Mission (SRTM), (ii) the new field-based method presented herein, and (iii) LiDAR data.

Fig. 5 Frequency distribution of the correlation coefficient between LiDAR and field methods DEM data in (a) Mt Field and (b) North Styx plot sites, displaying consistently high correlation values in both cases.

Fig 1.

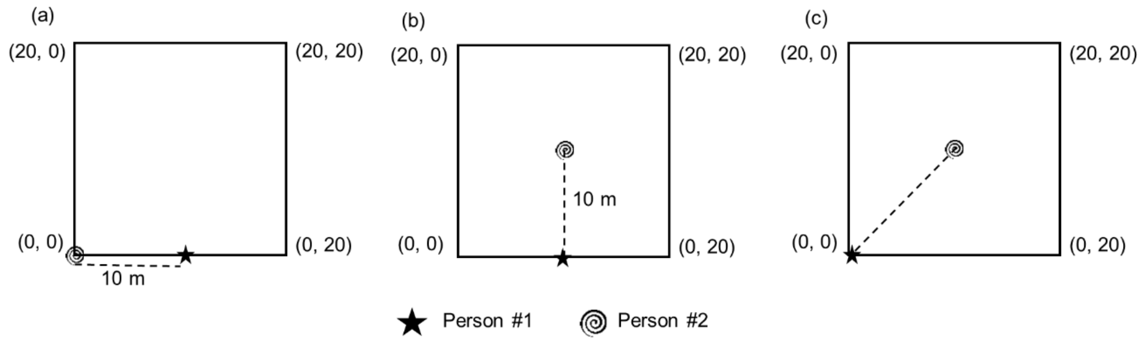

(a)
(20, 0)
(20, 20)
(0, 0)
(0, 20)
10 m
(b)
(20, 0)
(20, 20)
10 m
(0, 0)
(0, 20)
(c)
(20, 0)
(20, 20)
(0, 0)
(0, 20)
Person #1
Person #2

Fig 2.

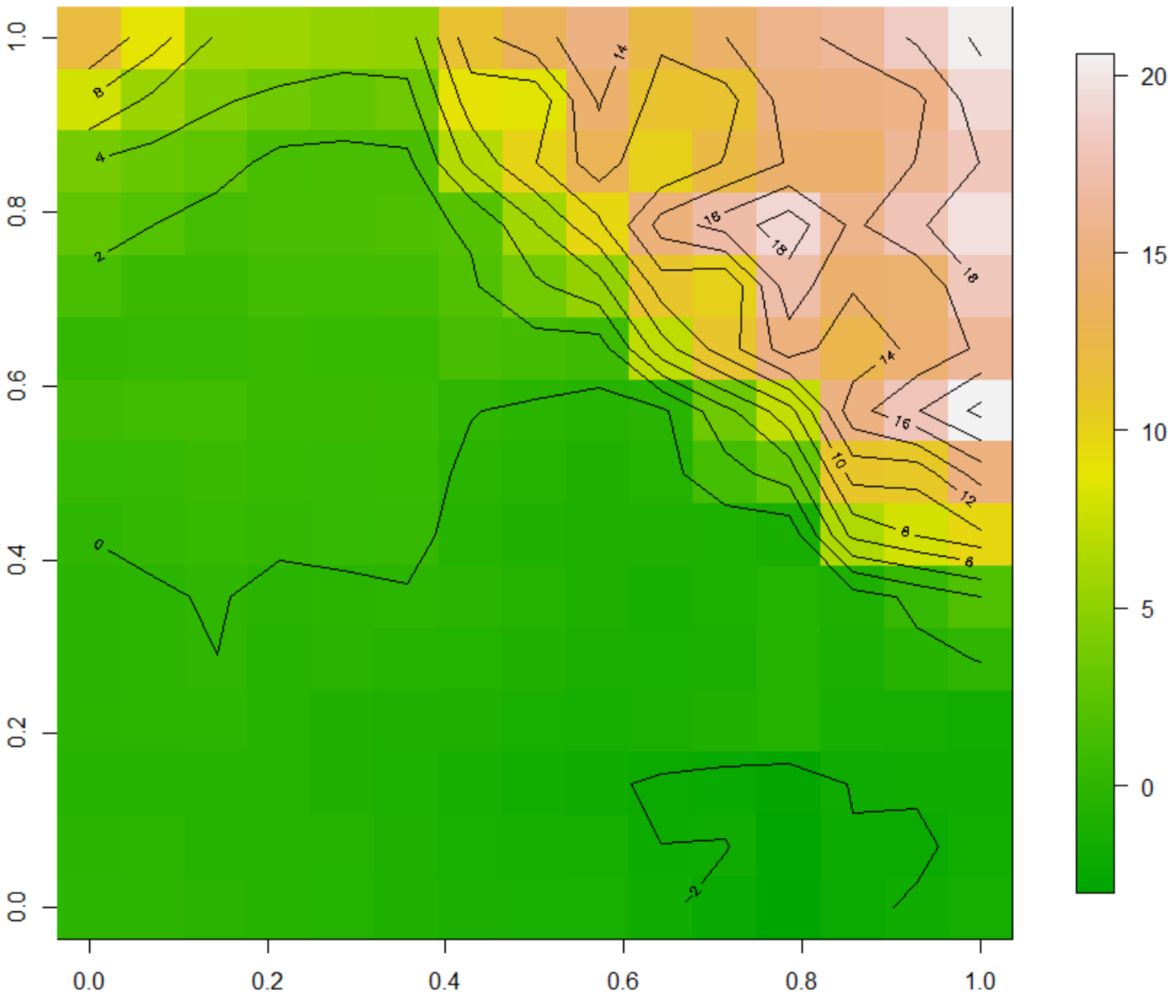


Fig 3.

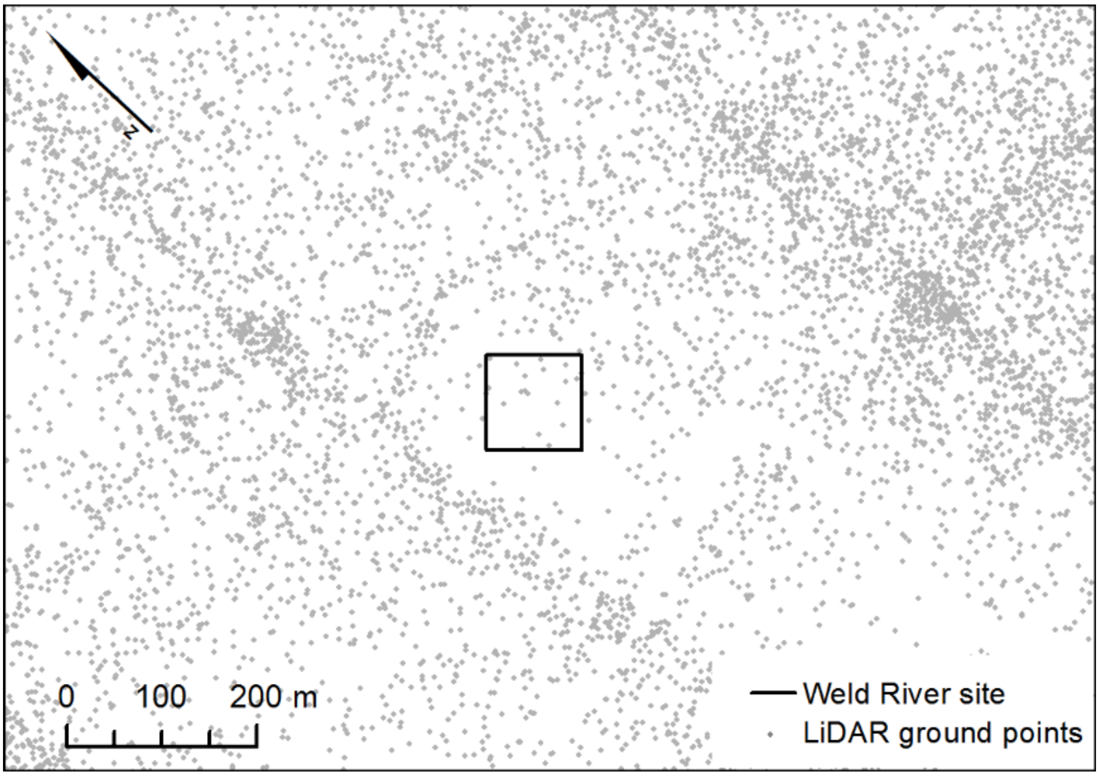
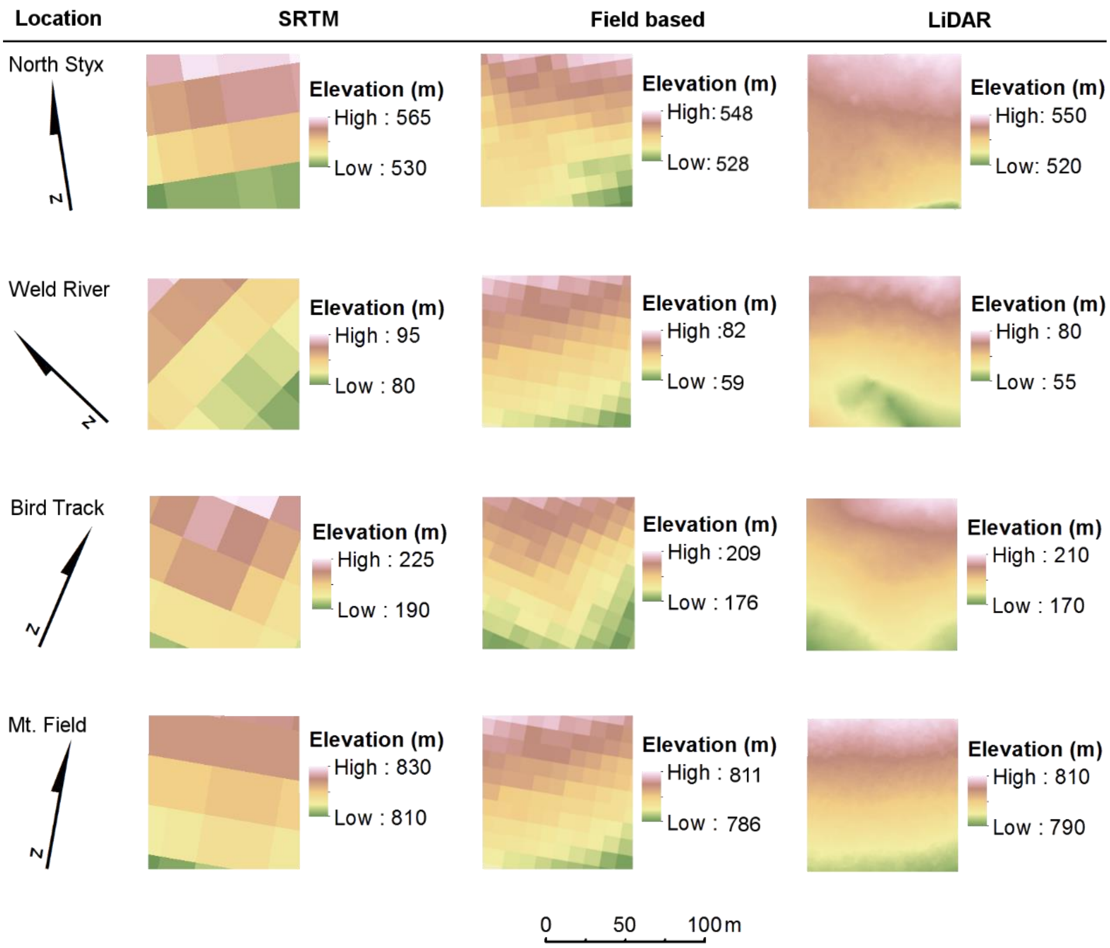
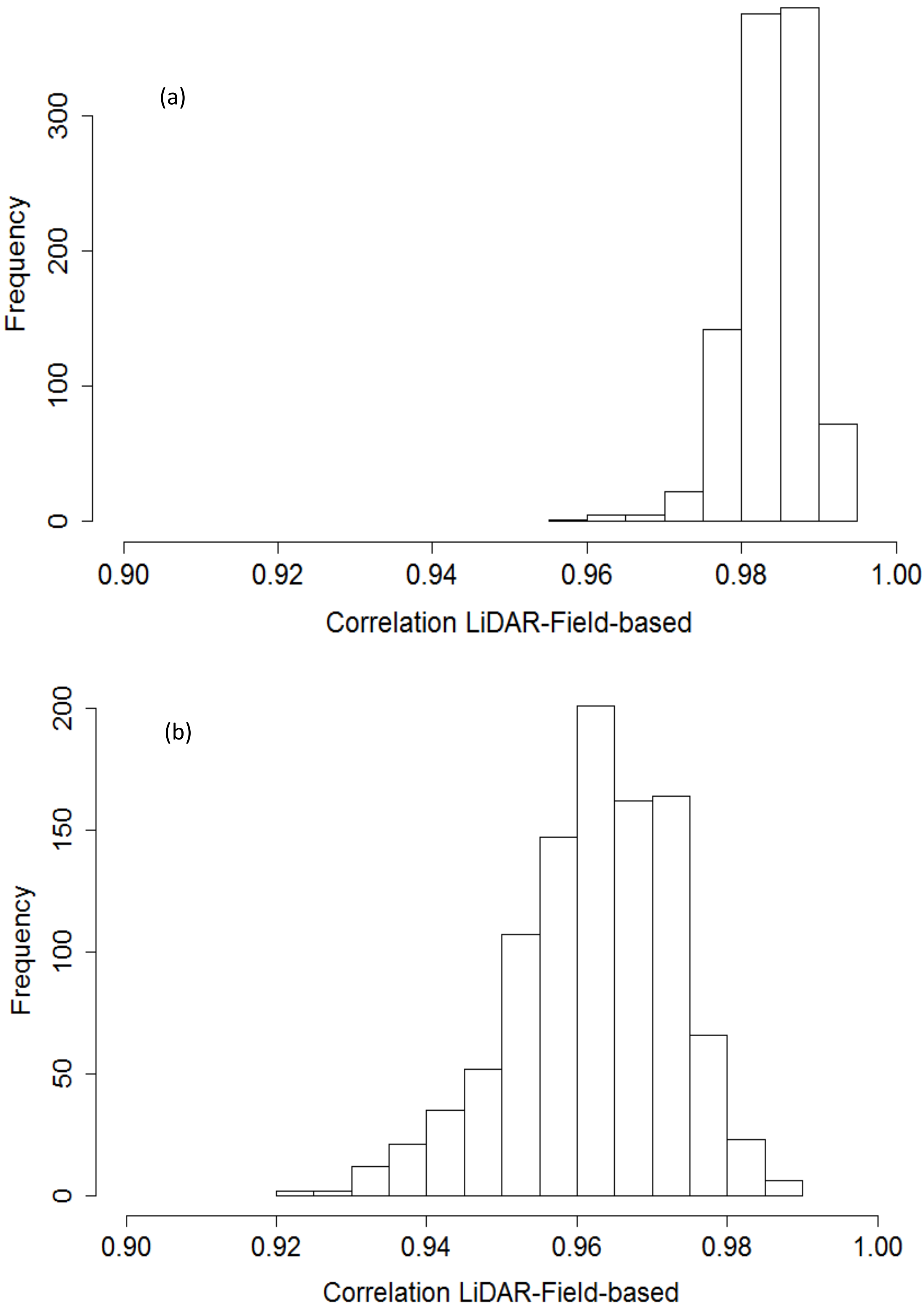


Fig 4.



Location
SRTM
Field based
LiDAR
North Styx
N
Elevation (m)
High : 565
Low : 530
Elevation (m)
High: 548
Low: 528
Elevation (m)
High: 550
Low: 520
Weld River
N
Elevation (m)
High : 95
Low : 80
Elevation (m)
High :82
Low :59
Elevation (m)
High : 80
Low : 55
Bird Track
N
Elevation (m)
High : 225
Low : 190
Elevation (m)
High : 209
Low : 176
Elevation (m)
High : 210
Low : 170
Mt. Field
N
Elevation (m)
High : 830
Low : 810
Elevation (m)
High : 811
Low : 786
Elevation (m)
High : 810
Low : 790
0
50
100 m

Fig 5.


(a)
Frequency
300
200
100
0
0.90
0.92
0.94
0.96
0.98
1.00
Correlation LiDAR-Field-based
(b)
Frequency
200
150
100
50
0
0.90
0.92
0.94
0.96
0.98
1.00
Correlation LiDAR-Field-based

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