Monitoring forestry outcomes in NSW native forests using airborne LiDAR

Methods and preliminary results

October 2023

Final Report

Enquiries

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Acknowledgement of Country

The Natural Resources Commission acknowledges and pays respect to traditional owners and Aboriginal peoples. The Commission recognises and acknowledges that traditional owners have a deep cultural, social, environmental, spiritual and economic connection to their lands and waters. We value and respect their knowledge in natural resource management and the contributions of many generations, including Elders, to this understanding and connection.

Acknowledgements

The Natural Resources Commission acknowledges the contribution of the following people for their advice in defining relevant LiDAR metrics and supporting the development of the analysis presented in this report: Professor Patrick Baker (University of Melbourne), Dr Geoff Horn (NSW Department of Planning and Environment) and Professor Scott Brown (University of Newcastle).

Citation

Brown, T., Hislop, S., Wall, J., Coates, Z., Liang, G., Voeste, J., Nguyen, A., Cooper, G. (2023) *Monitoring forestry outcomes in NSW native forests using airborne LiDAR*, NSW Natural Resources Commission, Sydney

Document No. D23/4411

List of acronyms

3D	three dimensions
ALS	Airborne Laser Scanning
AWS	Amazon Web Services
avg	average
BNA	Base Net Area
CHM	Canopy Height Model
Coastal IFOA	Coastal Integrated Forestry Operations Approval
cov	canopy cover
CRAFTI	Comprehensive Regional Assessment Aerial Photographic Interpretation
cv	coefficient of variation
DPI	Department of Primary Industries
EPA	Environment Protection Authority
FCNSW	Forestry Corporation of NSW
FMZ	Forest Management Zone
ha	hectare
HCVOG	High Conservation Value Old Growth forest
LiDAR	Light Detection and Ranging
MER	Monitoring, Evaluation and Reporting
m	metre
p95	95th percentile
P95 CHM	95th percentile used to create canopy height model values
NSW	New South Wales
sd	standard deviation
TIN	Triangulated Irregular Network
UAV	Unmanned Aerial Vehicle

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1 Introduction

The Coastal Integrated Forestry Operations Approval (Coastal IFOA) sets out the rules for native timber harvesting in New South Wales (NSW) coastal state forests and establishes the environmental outcomes that must be achieved under the approval. The Coastal IFOA requires that the approval conditions are monitored to ensure they are effective in achieving the required objectives and outcome statements.[1]

The Environment Protection Authority (EPA) and Department of Primary Industries (DPI) have jointly approved the Coastal IFOA Monitoring Program proposed by the NSW Forest Monitoring Steering Committee. The program sets out the broad framework to evaluate the effectiveness of priority conditions in meeting the Coastal IFOA objectives and outcomes. It centres on strategies to monitor and research forest health, biodiversity, water quality and aquatic habitat, and wood supply.

The program established key questions to focus monitoring on the Coastal IFOA objectives and outcomes. Landscape-scale monitoring questions include:

- Do harvesting conditions establish an appropriate mosaic of forest age classes at the landscape scale?
- Are the conditions maintaining functional connectivity for focal fauna species to move within and across the forest?
- Are the conditions effective in ensuring regenerating forests meet benchmarks for: (i) floristic composition (ii) forest structure (iii) coarse woody debris?
- Do the conditions establish enough key habitat features to maintain fauna species within and across the forest?
- To what extent are the conditions effectively managing the risk of new or existing areas subject to dieback?
- To what extent do the Coastal IFOA conditions maintain species occupancy in the landscape?
- Are the conditions affecting current commitments to meet wood supply?
- Are the conditions effectively promoting regeneration for long-term sustainable wood supply?

Understanding changes in forest structure at the local and landscape scale is critical to effectively answering these questions. This is supported by analysis of remote sensing data and integration with other spatial and non-spatial data.

1.1 Remote sensing supports landscape-scale monitoring

Multiple remote sensing methods are used in NSW to monitor public and private native forests, including passive and active sensors to assess the structure and condition of forest vegetation.

Passive sensors measure reflected energy from the sun or energy emitted from an object (i.e. heat). Passive sensors include cameras operating in the visible spectrum and multi-spectral instruments which typically collect information in the visible, near infrared and (sometimes) thermal infrared portions of the electromagnetic spectrum.

[1] Coastal IFOA Conditions (Chapter 8) and Coastal IFOA Protocols (Protocol 38).

Active sensors transmit energy directly and measure the returning signal. Active sensors include radar, sonar and LiDAR (Light Detection and Ranging).

Sensors can be mounted on ground-based platforms, airborne platforms (i.e. aircraft, unmanned aerial vehicles (UAVs)) or satellites – which affects the area able to be captured and the resolution of data captured.

Once collected, remotely sensed data must be processed into products and information to provide knowledge and insights to support decision-making.

A detailed discussion of the types and suitability of remote sensing methods for monitoring NSW native forests was prepared by Hislop and Stone (2023) to support the development of the NSW Private Native Forestry MER Framework[2].

1.2 Airborne LiDAR enables landscape-scale forest structure analysis

Airborne LiDAR (Airborne Laser Scanning; ALS) allows the 3D structure of forests to be evaluated across large areas with reduced effort and costs compared to ground-based measurements, and for some parameters at greater accuracy than by field crews using manual methods.

Forest structural metrics derived from ALS can be categorized into four main categories:

- cover
- height
- horizontal variability
- vertical variability

These 3D metrics can be combined with other spatial and non-spatial datasets to describe how forest structural characteristics relate to forest values and disturbance history.

1.3 New airborne LiDAR available for NSW coastal state forests

New ALS data and co-incident high-resolution imagery were captured across 250,000 ha of state forests in eastern NSW between August 2022 and April 2023 (Figure 1).

Sites were selected to cover the range of forest types, areas burnt and unburnt during the 2019-20 wildfires, fauna monitoring sites, forest inventory plots, completed and proposed harvesting areas, and areas managed for conservation.

[2] Hislop, S. & Stone, C. (2023) *Remote sensing of NSW private native forests – options and feasibility*, Report prepared for the NSW Natural Resources Commission, Sydney

Figure 1 – Airborne LiDAR capture areas over state forests in 2022 and 2023

2 Methods used to process and analyse ALS data

The Natural Resources Commission chaired a small working group comprised of experts in forest-based spatial and remote sensing analysis to advise on suitable ALS-derived metrics and methods to answer the key monitoring questions. The working group was comprised of:

- Professor Patrick Baker, The University of Melbourne
- Dr Geoff Horn, NSW Department of Planning and Environment
- Dr Sam Hislop, FLINTpro, Mullion Group
- Dr Julian Wall, 2rog
- Tony Brown, Forestry Corporation of NSW

This section outlines the methods used to process the ALS data into spatial layers and the subsequent analysis undertaken by the working group and a team from the University of Newcastle.

2.1 Airborne laser scanning (ALS) data acquired in 2022 and 2023

The ALS data were acquired by Aerometrex Pty Ltd, using a RIEGL VQ-780II sensor, at different times throughout 2022 and 2023 (Table 1).

The ALS data has a point density of approximately 30 points per m^2 and was delivered by the supplier in a point-cloud (LAS) format, split into tiles of 500m x 500m.

Table 1 – LiDAR capture areas and dates

Area	Acquisition dates
Casino	23/06/2022 to 25/06/2022
Coffs Harbour	07/07/2022
Styx River	08/07/2022
Bulahdelah	23/08/2023
Batemans Bay	21/04/2023 to 04/05/2023
Eden	01/08/2022
Wauchope	06/08/2022 to 23/11/2022 03/03/2023 (re-fly of small portion)

The state forests covered by each capture area are listed in Appendix 1.

2.2 LiDAR data processing methods

This data was processed using the LidR package in R package LidR (Roussel et al. 2020) on an Amazon Web Services (AWS) machine supplied by Forestry Corporation of NSW (FCNSW). LidR enables efficient parallel processing of large LiDAR datasets.

The processing steps, including code, are outlined in detail in the Appendix 2: ALS processing steps in R. They are briefly described here.

2.2.1 Height normalisation

LiDAR discrete return sensors emit laser pulses and measure the time taken for the reflected energy to return to the sensor. From the elapsed time, the distance between the sensor and object can be calculated. Because tree canopies contain many gaps, each pulse may have multiple returns. The 'first' returns are more likely to be the points that represent the forest canopy, while 'last' returns often indicate the ground.

Height normalisation replaces the Z (height) value for every point from an absolute measure (i.e., above sea level) to a relative measure from the ground. The normalised point cloud can then be used to determine the height of vegetation (Figure 2).

Prior to calculating relative heights, however, the ground surface must be modelled. Here, a triangulated irregular network (TIN) method was used to create the ground surface model. In a TIN, each 'ground' point is triangulated from its closest two points to create a surface. Because we only want to triangulate between ground points, the point cloud needs to be classified prior to this function being run. The data from the supplier is usually already classified into basic classes (ground, vegetation).

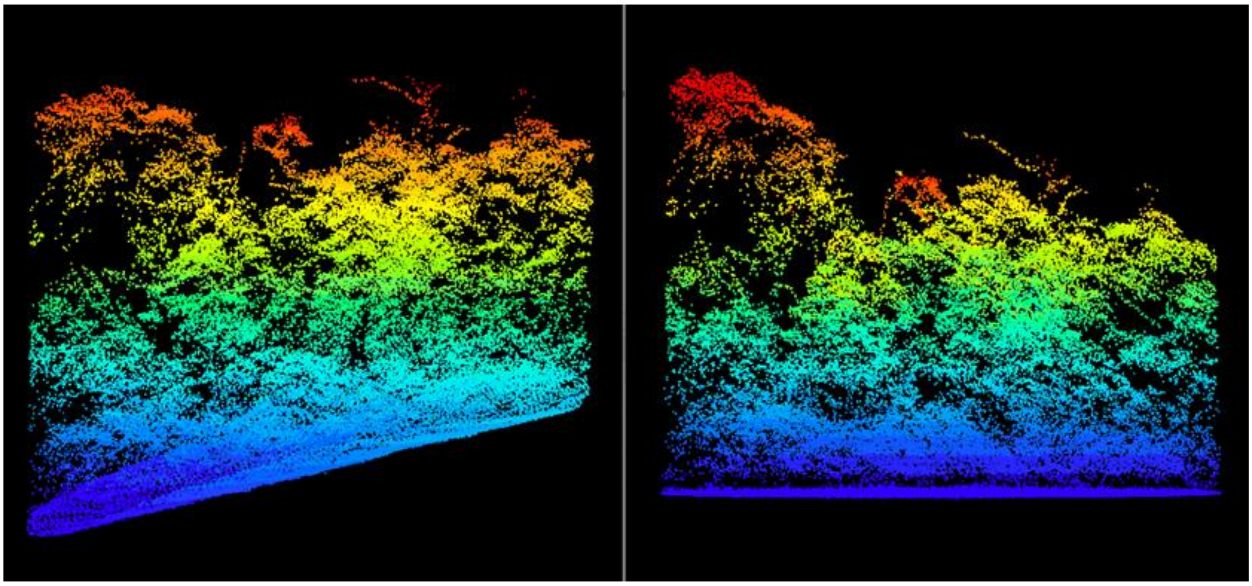

Figure 2 - Example of an initial point cloud (left) and a height normalized point cloud (right)

2.2.2 Canopy height models

A canopy height model (CHM) is a 2-dimensional representation of canopy height across an area (e.g., the LiDAR coverage extent) (Figure 3).

There are many different methods in the literature for generating CHMs. The simplest, conceptually, is to place a grid with a cell size of, for example, 1m across the area and take the highest point in each cell. However, this can lead to canopy 'pits' and a poor-quality output which looks speckled.

Here, the 'pit-free' algorithm of Khosravipour et al. (2014) was used to generate a smoother, more realistic output. After running the algorithm, a few individual pixels were unmapped (no-data). These were filled based on the mean of the surrounding 8 pixels using the R package terra (Hijmans 2023).

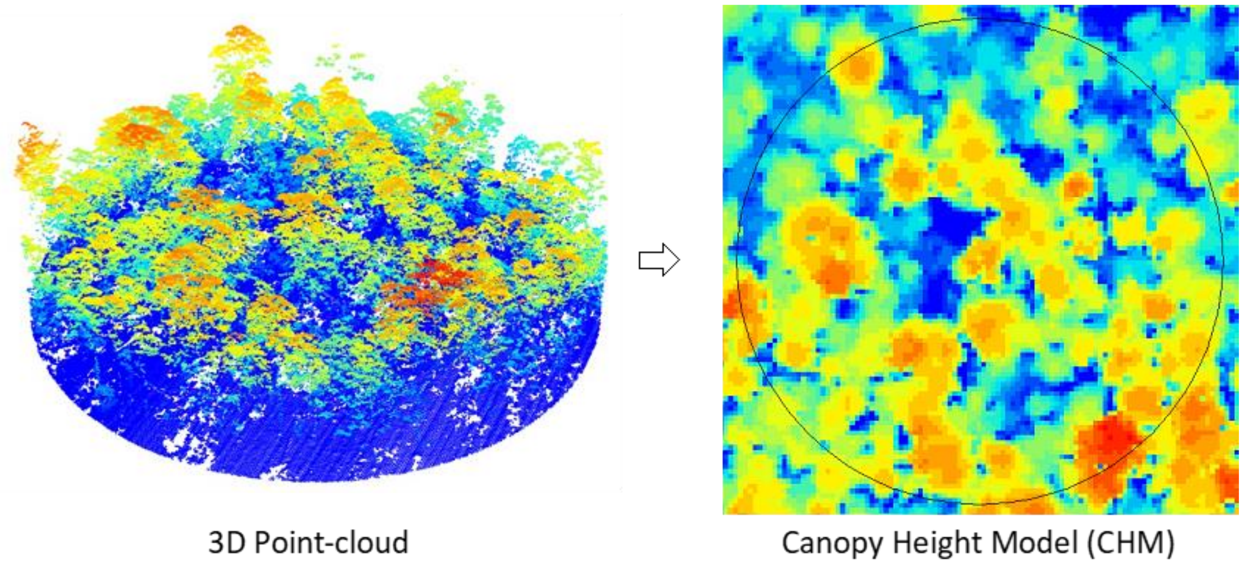

Figure 3 - Example of a 3D point-cloud (left) and canopy height model (right)

2.2.3 LiDAR metrics

LiDAR metrics are summary statistics of all the points in a specified area, typically based on the distribution of height values (vertical profile) (Figure 4).

Here, the Z-values (height) are summarised across the landscape using a 30m grid. Therefore, in each 30 x 30 m cell, all the points in that cell are summarised into a single value (e.g., the 95th percentile, the mean, etc.) with the output being a raster surface.

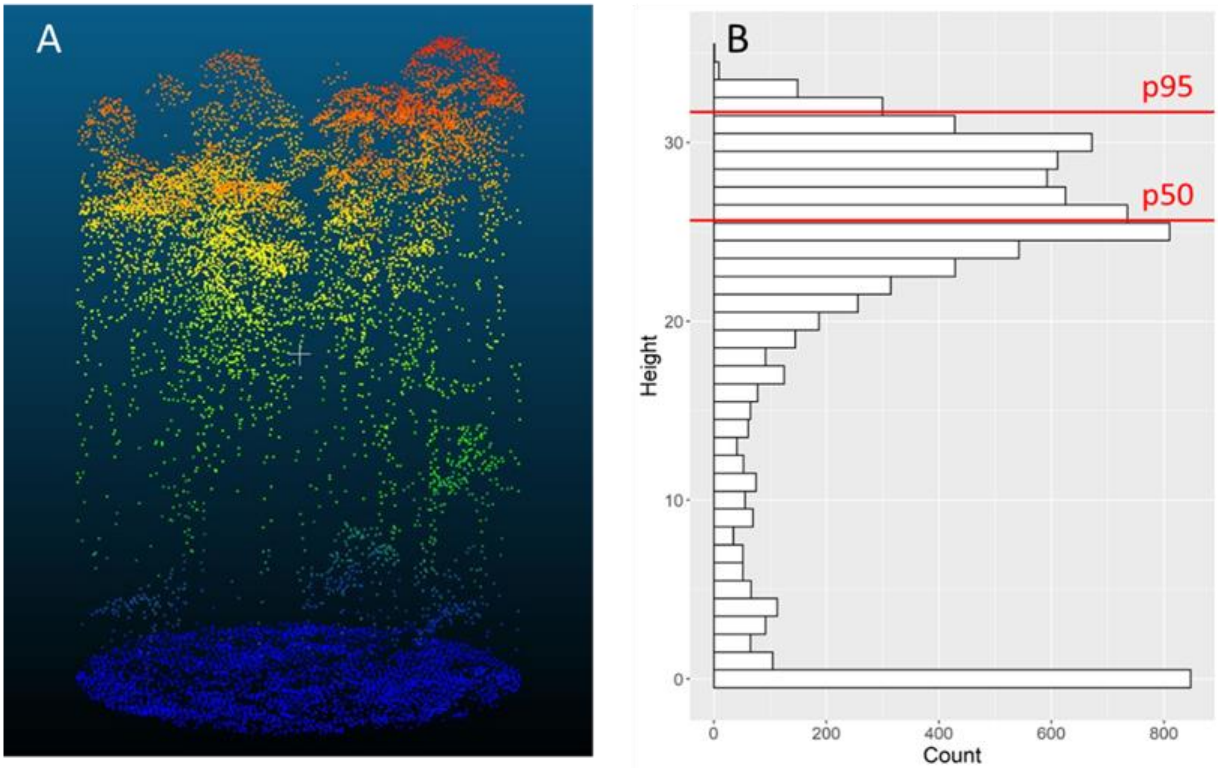

Figure 4 - Example of a 3D point cloud (left) and the corresponding distribution of height values (right), with the 50th and 95th percentiles shown in red

In this analysis, the first returns only were used to generate the LiDAR metrics shown in Table 2.

Table 2. LiDAR metrics created for this analysis

Metric	Details
Canopy cover (%)	Calculated as the number of first returns over 2m divided by all first returns
Canopy top height (m)	The 95th percentile height of first returns
Average canopy height (m)	Average height of first returns
Standard deviation (m)	Standard deviation of first returns
Skewness (m)	Skewness of first returns (i.e., whether more points are in the upper strata (negative skew) or lower (positive skew)
Coefficient of variation (m)	The standard deviation divided by the average height

2.2.5 Forest structure index

FCNSW has developed a ‘forest structure index’, which uses the 1m CHM to produce a surface representing forest structure across a broader landscape.

The steps to create the structure index are:

1. Square the CHM value for each 1m pixel

23	24	26	25	24	24	23	22	19	23
24	31	29	28	30	28	25	24	26	25
28	26	25	31	31	28	30	27	25	27
25	26	29	25	32	28	26	31	30	23
30	26	29	28	32	32	28	32	31	25
30	32	24	28	26	23	26	33	27	30
24	32	25	29	28	24	26	28	23	30
26	24	31	28	30	25	26	32	27	33
24	25	26	27	28	29	30	31	32	25
26	28	29	26	25	25	26	27	26	26

529	576	676	625	576	576	529	484	361	529
581	955	822	760	871	763	605	585	654	616
759	693	608	981	943	761	927	753	636	737
607	675	856	617	1005	758	667	970	882	541
903	696	816	778	1035	993	759	1003	942	642
874	999	558	775	674	545	670	1060	709	891
568	1036	622	832	761	560	689	782	551	928
662	558	958	772	915	644	680	1040	751	1087
576	625	676	729	784	841	900	961	1024	615
695	796	851	697	604	621	672	747	685	678

2. Aggregate to 5m pixels, using the sum of squared CHM values for each 1m pixel

18943	18943	18943	18943	18943	17672	17672	17672	17672	17672
18943	18943	18943	18943	18943	17672	17672	17672	17672	17672
18943	18943	18943	18943	18943	17672	17672	17672	17672	17672
18943	18943	18943	18943	18943	17672	17672	17672	17672	17672
18943	18943	18943	18943	18943	17672	17672	17672	17672	17672
18597	18597	18597	18597	18597	19332	19332	19332	19332	19332
18597	18597	18597	18597	18597	19332	19332	19332	19332	19332
18597	18597	18597	18597	18597	19332	19332	19332	19332	19332
18597	18597	18597	18597	18597	19332	19332	19332	19332	19332
18597	18597	18597	18597	18597	19332	19332	19332	19332	19332

18943	17672
18597	19332

4. Create a focal sum using a 9x9 pixel window (i.e. 81, 5m pixels). Where the output value for an individual 5m pixel is the sum of the input values for itself and the surrounding 80 cells. The image below shows the pixels used to calculate the focal sum (top) and the diagonally adjacent output values (bottom).

17672	26633	38378	51740	58912	53177	22920	29855	19808	27894	33618	35823	43739	21091	38417
19332	29673	26164	27906	23173	33889	42994	25999	18886	27932	28791	24717	37897	55151	27472
28211	44135	20849	52544	58174	44934	35924	22317	26279	32466	26083	40883	53130	37467	35315
31402	30857	35561	36663	39487	28194	58201	37189	23333	41420	40045	35742	26100	49414	24584
43286	36122	37891	51691	74076	44280	24003	35338	22602	47067	37631	54492	23617	55269	35695
49476	43812	43998	50832	36388	46579	58475	36398	37300	49139	53183	38084	36344	58785	43289
27902	47346	20822	23248	84361	28485	35875	34223	32030	64497	49166	20405	24822	53133	53148
54185	52461	24494	61745	28989	50134	69815	38461	19961	27084	45368	34018	20951	52342	31565
30185	50459	26113	36090	84245	42156	23487	45099	33181	20402	29463	26894	42560	27883	29939
57724	23590	34812	64344	45256	51119	28439	22160	37373	22699	45928	40016	35427	31748	38437
43895	68632	27505	25043	45894	45364	25417	38241	34534	35754	35743	20701	29741	45609	22535
67591	38180	21793	57950	24298	60587	29000	25230	47538	24430	27996	41519	31043	21800	23772
48499	45448	35008	36654	59346	19719	36742	24035	52053	21021	23279	30090	40508	48717	19640
42980	19695	29544	23179	20015	47005	44965	40869	21137	32389	37734	19699	48928	36696	30846
65207	44688	27745	42140	49428	38468	20628	28476	19138	24290	39371	23598	41407	25470	31917
22923	24249	32840	35543	32379	50398	62321	38226	26524	27937	39706	34802	60554	30288	28672
53743	59377	40354	20699	36972	30462	35374	41783	21551	33753	29141	32708	30019	34997	37355
29728	40984	31800	42820	50633	30705	58219	52916	39258	35365	32224	44078	37938	28859	34590
39207	72713	55828	23945	48363	22860	29952	58288	40118	41319	33720	41142	31935	39973	21755

1050600	1255074	1439115	1589813	1590652	1627530	1626278	1659090	1623028	1587599	1544607	1530781	1649583	1705696	1701099
1302544	1553597	1796113	1983208	1993910	2030450	2038569	2065467	2014917	2001884	1955603	1920028	2051408	2112711	2112893
1526768	1806305	2084697	2306015	2328202	2401338	2411277	2437757	2388781	2344521	2322903	2281424	2413551	2476011	2456562
1791007	2120679	2468885	2728664	2728448	2774482	2777328	2813333	2723563	2702655	2662468	2586484	2728704	2795552	2796903
2038835	2410664	2782356	3087235	3099464	3135716	3117565	3154351	3071051	2993781	2941376	2863274	2984600	3066532	3092592
2092299	2462069	2839281	3136464	3145186	3136191	3133393	3177937	3073721	3020765	2970439	2881705	2999788	3058916	3089612
2192070	2573316	2932950	3242375	3251694	3225958	3191153	3230340	3120832	3035612	2968874	2902925	3030755	3072075	3115507
2217906	2614805	2967516	3279854	3290496	3217344	3190407	3229288	3092286	3025276	2931341	2890439	3018381	3017033	3078265
2291329	2679753	3011005	3310189	3327114	3216465	3158171	3191953	3069368	2981802	2891399	2866088	3022288	2995141	3075597
2215626	2606775	2958989	3263704	3247212	3122191	3080429	3087765	3019003	2966924	2868948	2828132	2962120	2950209	3032875
2250566	2633604	2947971	3244765	3179871	3014271	2957820	2966923	2911917	2813483	2712246	2713202	2841789	2844363	2951177
2213462	2618413	2959226	3260022	3170982	2973800	2930986	2942469	2910899	2841603	2693976	2674747	2809582	2829319	2954408
2204515	2589794	2896165	3200284	3111051	2920979	2855023	2849336	2867880	2773256	2651092	2680580	2813456	2836227	2934990
2196095	2569923	2911027	3222962	3117098	2942447	2888727	2894537	2901729	2841693	2735630	2754403	2912063	2909680	2976952
2218607	2564176	2906793	3254857	3143555	3006041	2890989	2876910	2921009	2866090	2771603	2778076	2900175	2875851	2941585
2135410	2461877	2812290	3168002	3065475	2948777	2894959	2878100	2914692	2858309	2789938	2811679	2958545	2950544	3001402
2131691	2422276	2780285	3144088	3008248	2904253	2834046	2795769	2855117	2807633	2770382	2769932	2902531	2925015	2988595
2064865	2364945	2726219	3124470	2979754	2926547	2869260	2850415	2891713	2863107	2839871	2882627	2957978	3006956	3033829
2099464	2380968	2727370	3136519	3010178	2935763	2856059	2843635	2870421	2841061	2840245	2895540	2926940	2948217	2991070

The result is a raster with 5m pixels where each cell represents the sum of the squared height across 0.2 ha. The resulting forest structure index is illustrated in Figure 5.

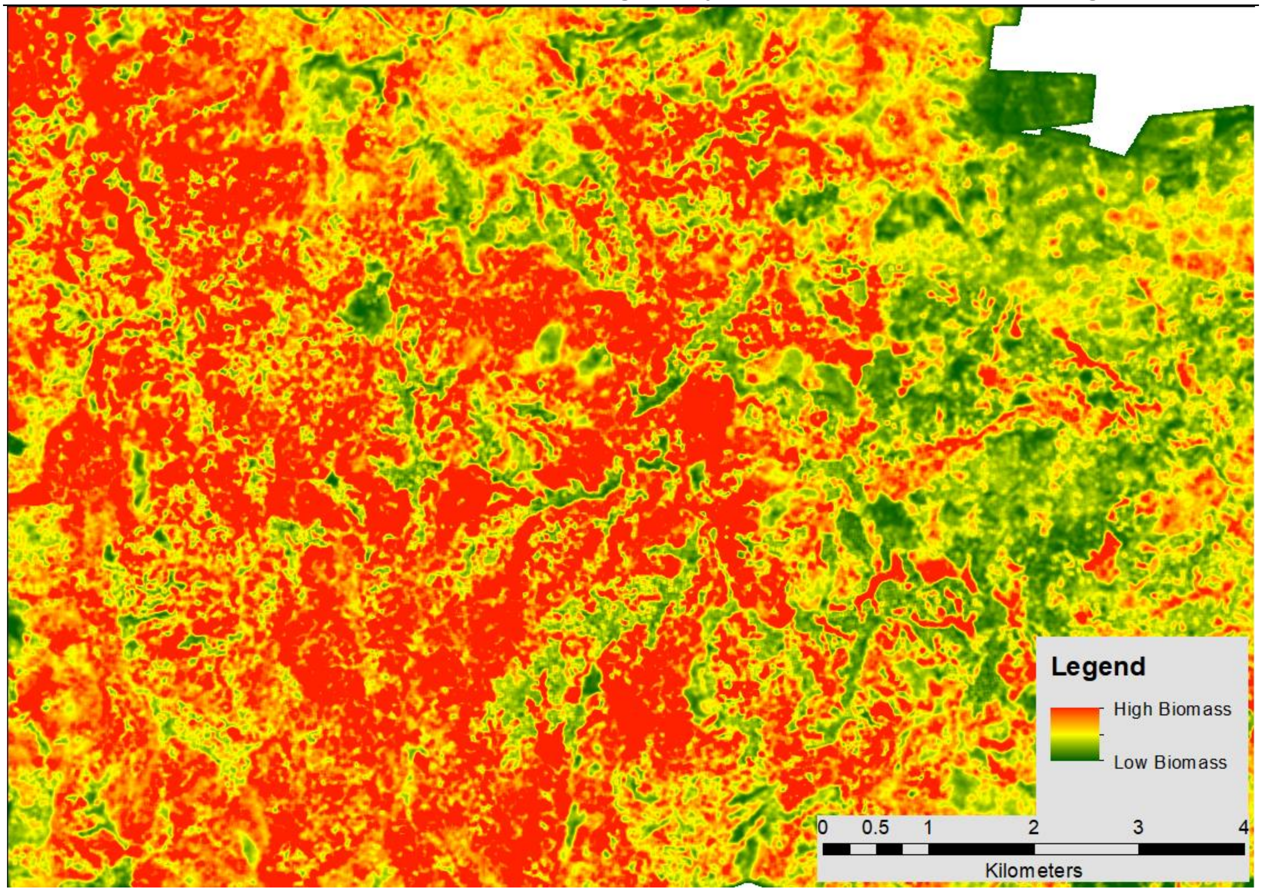

Figure 5 – Example forest structure index

2.3 Method to develop structural connectivity index

2.3.1 Context

The configuration and contiguity of native vegetation communities in a landscape, or conversely the degree to which natural systems have been fragmented through modification (e.g. intensive harvesting), are important factor when considering forest resilience and the persistence of native species.

Vegetation connectivity can be referred to as 'structural connectivity' which is simply an index of the connectedness of the native vegetation across landscapes[3], or 'functional connectivity' which relates to the ease with which processes such as species dispersal can operate.

Examples of structural connectivity include large connected patches, linear elements such as corridors, and partially vegetated drainage lines or fence lines. It may consist of more subtle habitat elements such as scattered trees, often referred to as "stepping stones" because of their scattered, non-linear structure[4].

Functional connectivity is distinguished from structural connectivity in the context that conservation value accrues to patches or stepping stones only if animals in real landscapes

[3] Bélisle, M. (2005). Measuring landscape connectivity: the challenge of behavioural landscape ecology. *Ecology*. 86: 1988-1995.
[4] Doerr, V.A.J., Doerr, E.D. and Davies, M.J. (2010). *Does structural connectivity facilitate dispersal of native species in Australia's fragmented terrestrial landscapes?* Systematic Review No. 44, Collaboration of Environmental Evidence. CSIRO. Canberra.

use them to bring about connectivity[5]. Patches of native vegetation are connected functionally if a species can cross the non-habitat area (matrix) between those habitat patches successfully[6].

Structural connectivity considers the structure of the forest-gap matrix, while functional connectivity considers the capacity of individual species to move within this matrix.

Functional connectivity is more complex because what is functionally connected for one species might not be for another species.

In this trial we consider structural connectivity only, and we make a broad assumption that for most species, ‘connected’ forested will be preferred over ‘fragmented’ forest, which will be preferred over ‘forest edge’, which will be preferred over forest gaps, for occupancy and movement.

2.3.2 Approach to develop connectivity index using 6m threshold

The CHM was reclassified into a binary patch layer with a 5x5m pixel resolution, based on a 6 m height threshold which is a recognised cutoff between ‘low’ trees and ‘mid-tall’ trees (Australian soil and land survey handbook[7]). The two classes were:

- ≥ 6m = 1
- < 6m = 0

The CHM was smoothed whereby any ‘1’ pixel that was entirely surrounded by ‘0’ pixels was converted to ‘0’, and any ‘0’ pixel that was entirely surrounded by ‘1’ pixels was converted to ‘1’.

A 30 m buffer was then established around each separate forest patch (connected groups of cells with value = 1), and concentric 30m buffers were created around these, demarking different distance bands to the nearest adjacent forest. The layer was then converted to a structural connectivity layer with 10 classes (Table 2).

[5] Beier, P. and Noss, R.F. (1998). Do habitat corridors provide connectivity? Conservation Biology. 12: 1241-1252.
[6] Tischendorf, L. and Fahrig, L. (2000). On the usage and measurement of landscape connectivity. Oikos. 90: 7-19.
[7] McDonald, R.C., Isbell, R. F., Speight, J.G., Walker, J. and Hopkins, M.S. (1984). Australian soil and land survey. Field handbook. Inkata, Melbourne. pp 165

Table 2 - Structural connectivity classes attributed to CHM-derived patch layer (height threshold = 6m)

Class[A]	Connectivity class	Description
1	Connected	Any forest patch ≥ 6m height that contains ≥ 30% forest cover within a 30 m buffer[B] around the patch, and ≥50% connected forest within a 30 m buffer[B]
1	Fragmented	Any forest patch ≥ 6m height that contains < 30% forest cover within a 30 m buffer[B] around the patch, or < 50% connected forest within a 30 m buffer[B]
0	Edge (0-30m)	Non-forest surrounding any patch, to a distance up to 30 m from the patch
0	Gap (30-60 m)	Non forest that is >30 to 60 m from a patch
0	Gap (60-90 m)	Non forest that is >60 to 90 m from a patch
0	Gap (90-120 m)	Non forest that is >90 to 120 m from a patch
0	Gap (120-180 m)	Non forest that is >120 to 180 m from a patch
0	Gap (180-240 m)	Non forest that is >180 to 240 m from a patch
0	Gap (240-300 m)	Non forest that is >240 to 300 m from a patch
0	Gap (>300 m)	Non forest that is >300 m from the nearest patch

A. ≥6m = 1; < 6m = 0
B. Spatial extent of the 30 m buffer includes the patch from which it was derived

2.3.3 Approach to develop connectivity index using 12m threshold

The CHM was also reclassified into a binary layer with a 5x5m pixel resolution, based on a 12 m height threshold, which is a recognised cutoff between 'mid-tall' trees and 'tall' trees (Australian soil and land survey handbook), and likely separates non-forest and early regrowth forest from advanced regrowth, mixed, mature and old forest. The two classes were:

- ≥12m = 1
- < 12m = 0

As with the 6 m threshold, the CHM was smoothed, then a 60 m buffer was established around each separate forest patch (patches with value = 1), and concentric 60 m buffers were created around these, demarking different distance bands to the nearest adjacent forest. The layer was then converted to a structural connectivity layer with eight classes (Table 3).

Table 3 – Structural connectivity classes attributed to CHM-derived patch layer (height threshold = 12m)

Class[C]	Connectivity class	Description
1	Connected	Any forest patch ≥12 m height that contains ≥15% forest cover within a 60 m buffer[D] around the patch, and ≥50% connected forest within a 60 m buffer[D]
1	Fragmented	Any forest patch ≥12 m height that contains <15% forest cover within a 60 m buffer[D] around the patch, or <50% connected forest within a 60 m buffer[D]
0	Edge (0-60m)	Non-forest surrounding any patch, to a distance up to 30 m from the patch
0	Gap (60-120 m)	Non forest that is >60 to 120 m from a patch
0	Gap (120-180 m)	Non forest that is >120 to 180 m from a patch
0	Gap (180-240 m)	Non forest that is >180 to 240 m from a patch
0	Gap (240-300 m)	Non forest that is >240 to 300 m from a patch
0	Gap (>300 m)	Non forest that is >300 m from the nearest patch

C. ≥12m = 1; <12m = 0
D. Spatial extent of the 60 m buffer includes the patch from which it was derived

Figure 6 provides an example of outputs across the Coffs Harbour area showing the reclassified CHM using the 6m threshold, and the derived structural connectivity surfaces for the 6m threshold. Figure 7 shows the same for the 12m threshold.

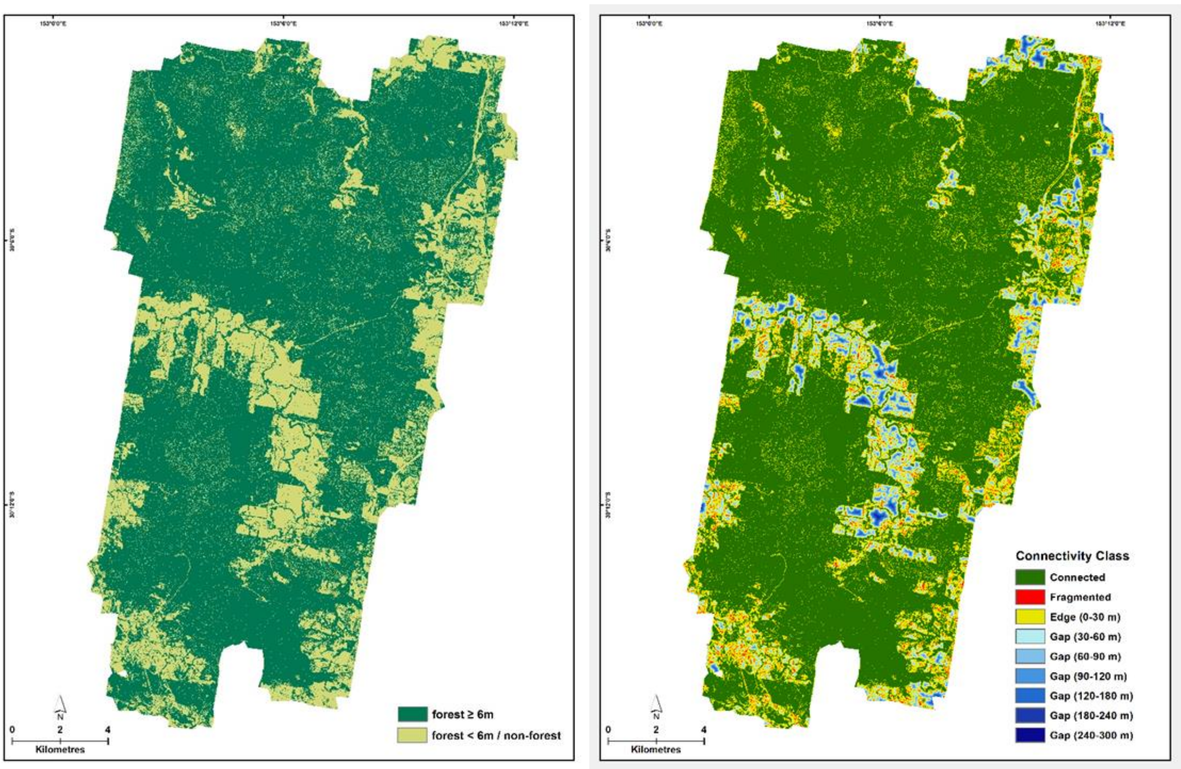

Figure 6 - Binary layer derived using the 6m height cut-off (left) and connectivity layer derived from the 6m cut-off data (right)

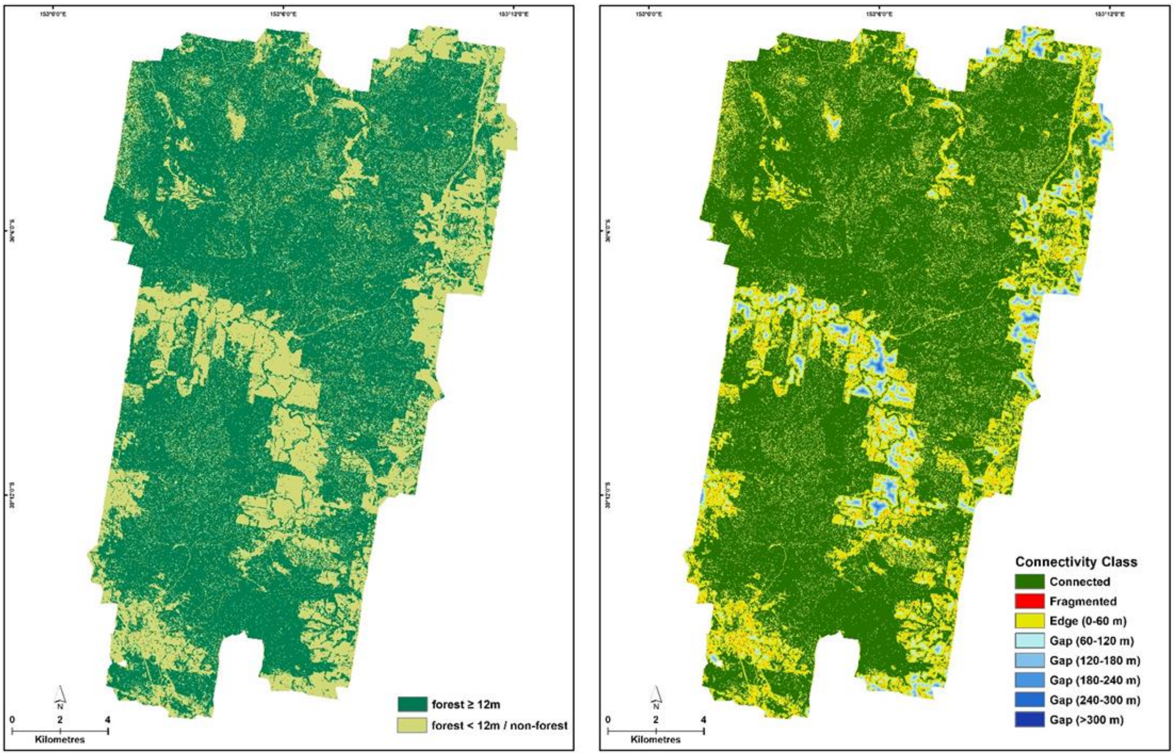

Figure 7 - Binary layer derived using the 12m height cut-off (left) and connectivity layer derived from the 12m cut-off data (right)

3 Interpretation of LiDAR outputs

The LiDAR metrics described in the previous section can be combined with other spatial data to add context and to allow deeper analysis of impacts of different natural and anthropogenic drivers of change.

It should be noted that the LiDAR data was captured between 2.5 and 3 years after the 2019/20 wildfires. During this time above average rainfall occurred across the LiDAR capture regions providing favourable conditions for forest recovery.

3.1 Exploring the relationship between time since harvest and LiDAR metrics

Time since last harvest was intersected with the LiDAR metric rasters (Figure 8). This, in a sense, swaps space for time.

By summarising the values of each LiDAR metric in the area harvested in a given year, it is possible to look at the relationship between time since harvest and vegetation structure. For example, how do areas ten years post-harvest compare with areas two years post-harvest?

The methods here required existing spatial datasets for harvest history in native forests and plantation data, which was used to mask out areas of plantation within the capture areas.

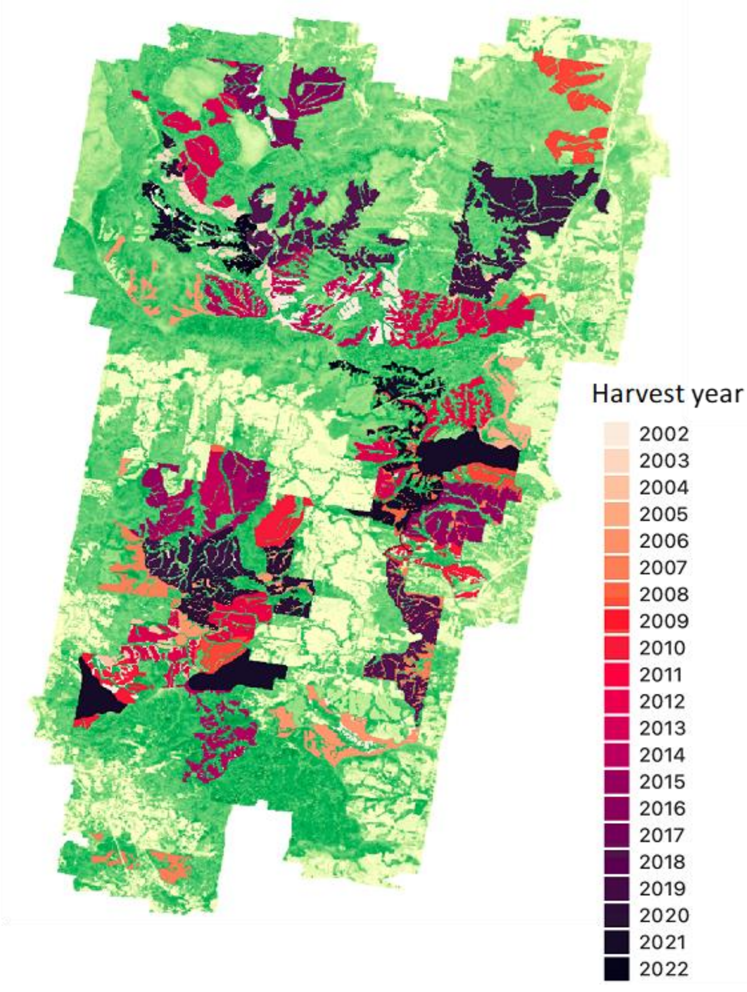

Figure 8 - The CHM for Coffs Harbour with recent harvest history overlaid

Outputs from this analysis are shown in Figure 9. Here, we can infer that canopy cover returns to its baseline state seven years after harvest, whereas canopy height takes more like 15 years.

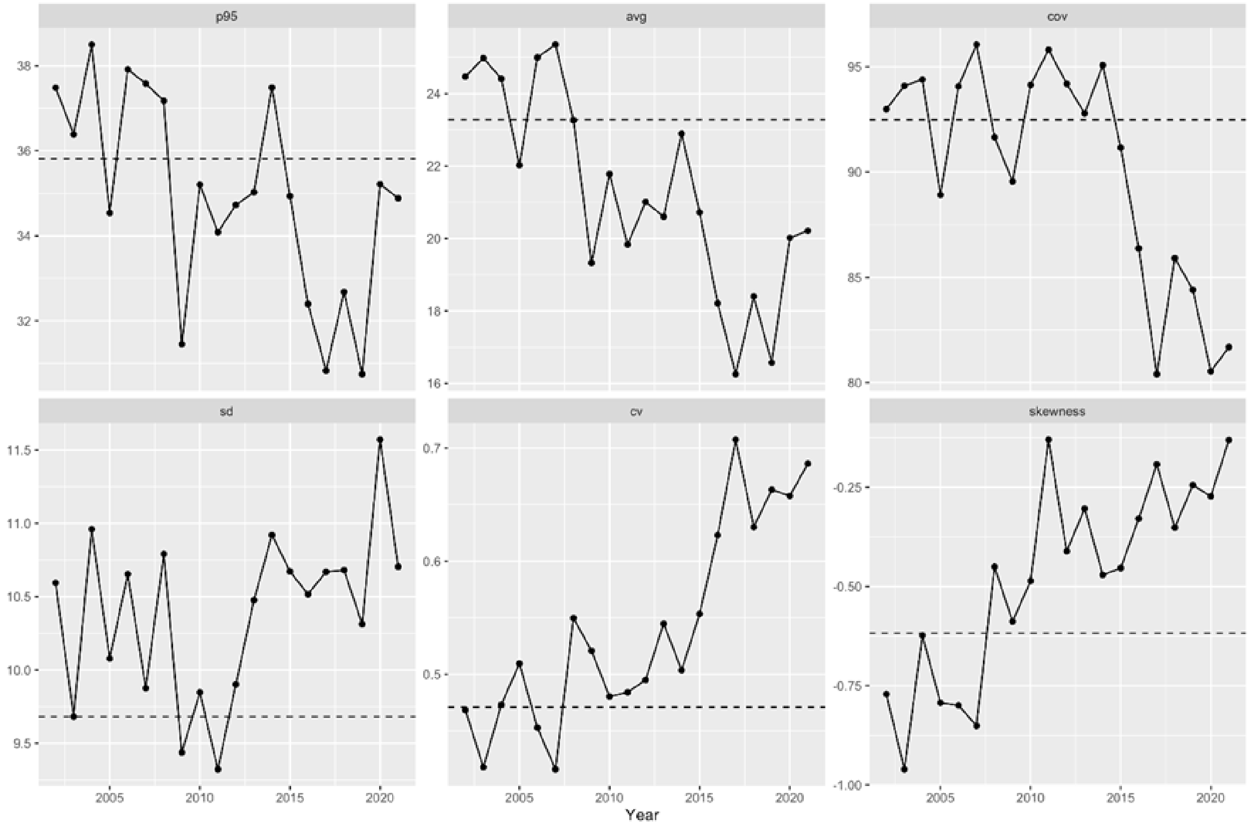

Figure 9 - Summary statistics based on time since harvest for Coffs Harbour, including LiDAR metrics for canopy top height (p95), average height (avg), canopy cover (cov), standard deviation (sd), coefficient of variation (cv) and skewness.

A similar analysis was conducted for each LiDAR capture area comparing mean top height (p95) and mean canopy cover within the base net area (BNA) and forests in the same area managed for conservation, using the method described in section 3.2. Figure 10 and Figure 11 show the mean top height (p95) and mean canopy cover respectively in each region by harvest year for each area of BNA.

Further exploration of the data is needed to account for different forest types commonly found in areas managed for conservation compared to forest within the BNA within the same operational area.

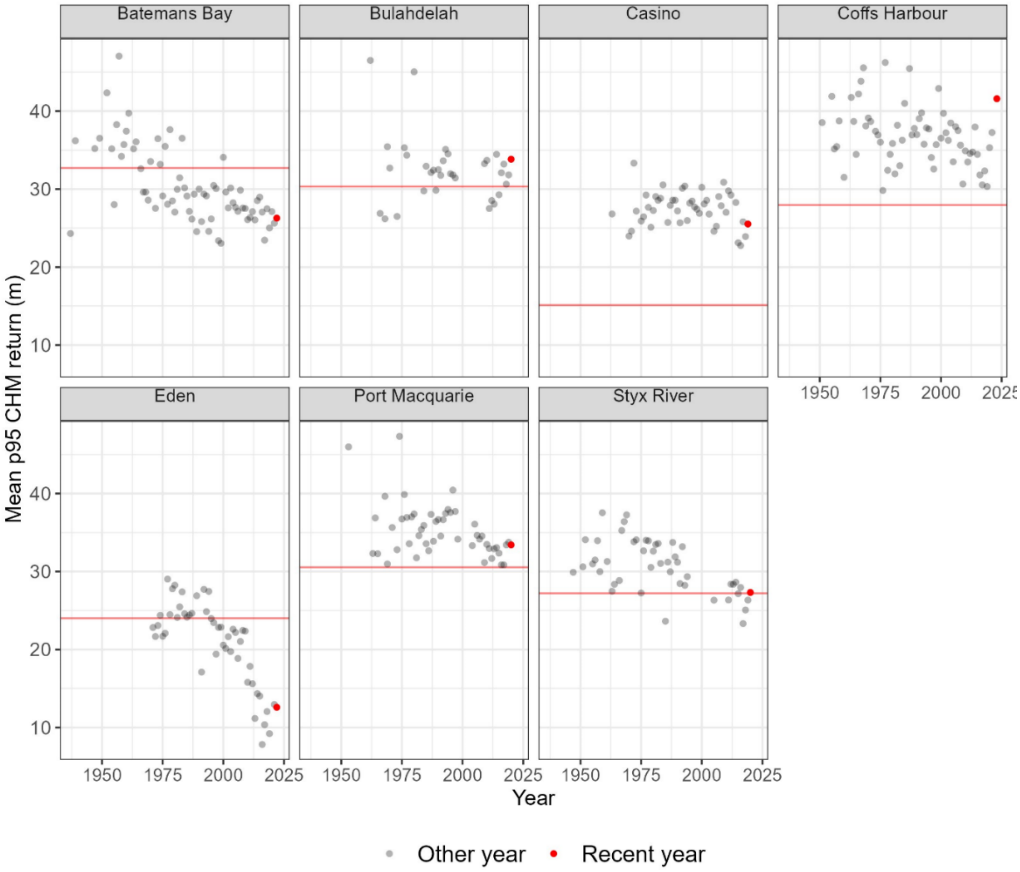

Figure 10 – Mean p95 CHM return for conservation areas (red line) and BNA by year harvested

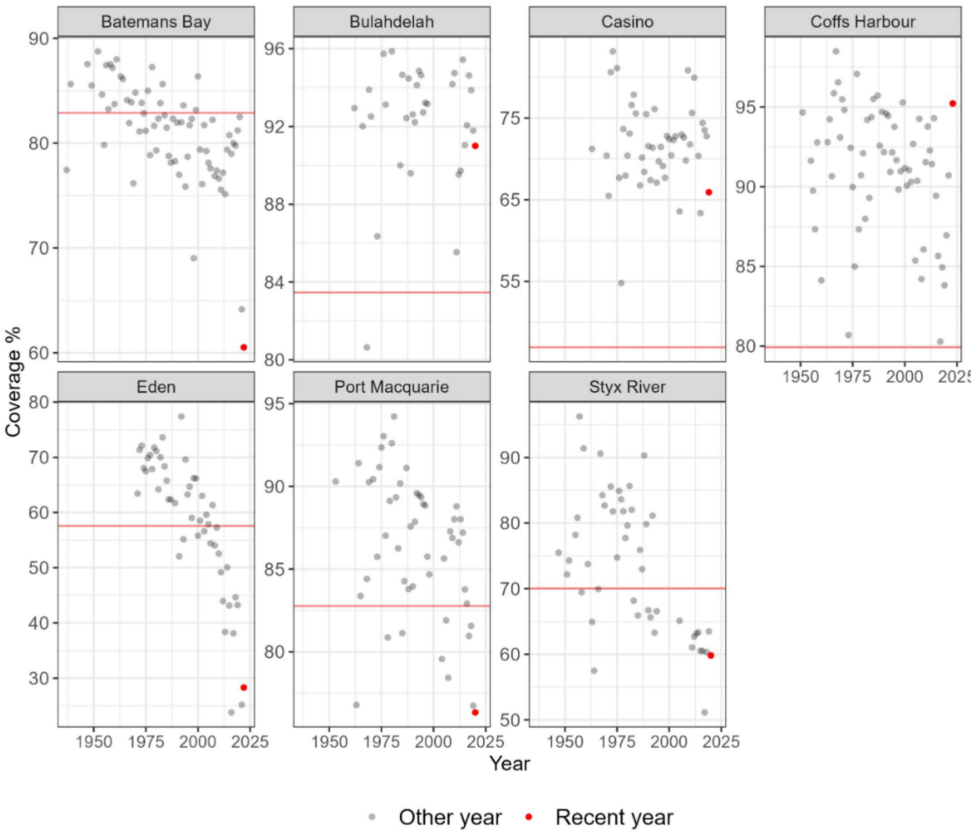

Figure 11 – Mean canopy cover for conservation areas (red line) and BNA by year harvested

3.2 Analysing LiDAR metrics and forest variability

Integration and analysis of spatial data and LiDAR metrics was conducted using R. Figure 12 provides an overview of the data preparation and processing steps. The R code used for the analysis is detailed in Appendix 2. The spatial data used in the analysis are listed in Appendix 3.

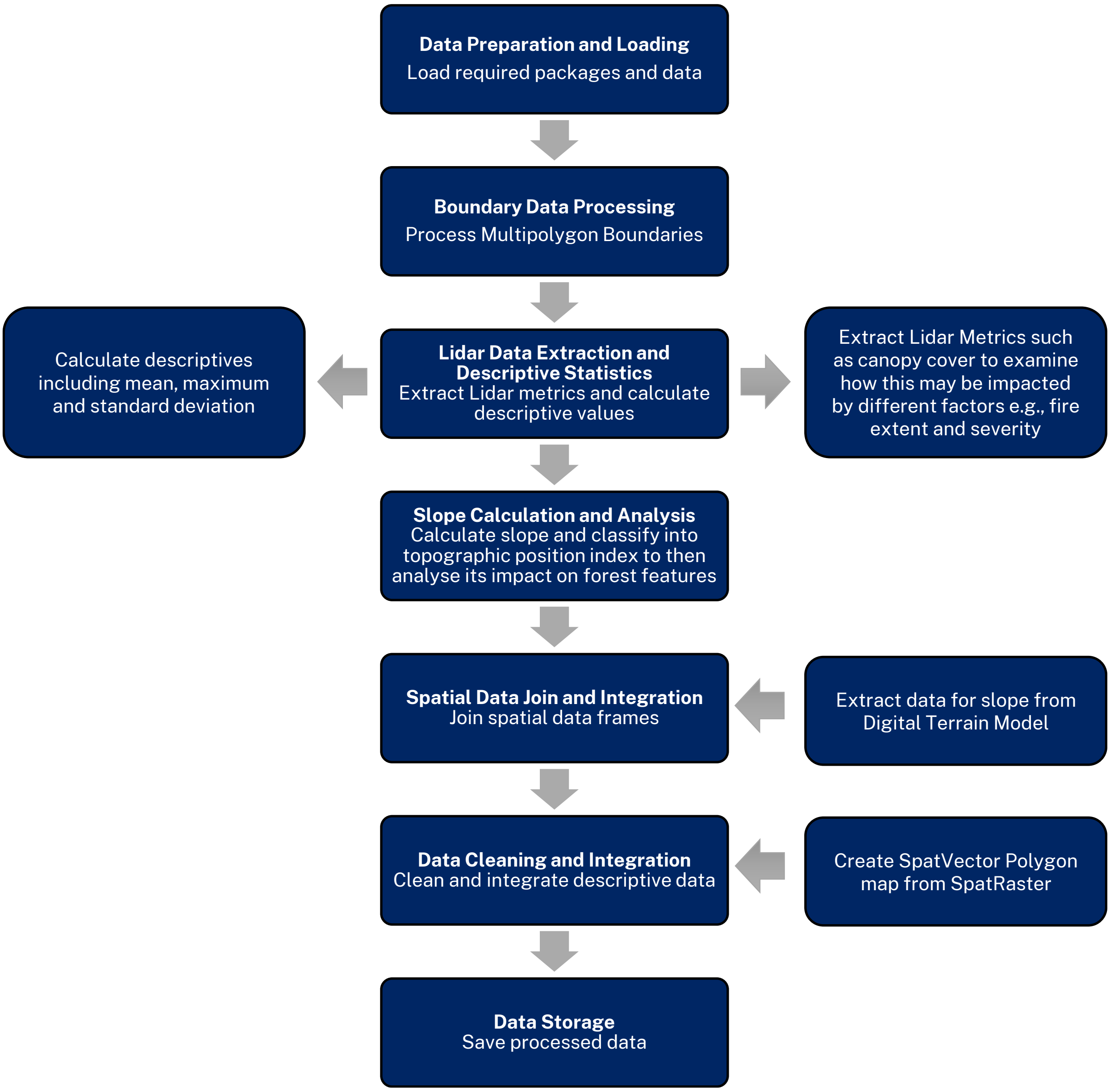

Figure 12 – Process used to prepare and analyse LiDAR metrics and other spatial data

SpatRasters are spatially referenced surfaces which store data within pixels. This is the process used for storing LiDAR data for extraction and analysis.

SpatVectors are used to store vector data such as points, polygons and other attributes. Geometry within a SpatRaster is identified by Polygons, often MultiPolygons. These Polygons are of varying shape and identify a specific location within the SpatRaster. This location is identified using a coordinate reference system (CRS).

Using SpatRasters of forest data and SpatVectors enables LiDAR metrics to be extracted, such as average CHM return or canopy cover, and examine what effects certain factors, such as fires or harvesting method, may have on forest variability. This process involves first, extracting data from the SpatRaster, which provides the associated LiDAR metrics for points in the SpatVector. From this the mean, max and standard deviation are extracted. The extracted data is then spatially joined to the SpatVector data frame by matching polygons within the same location. This is similar to how a left-join may work with a common variable.

The process of extracting data from SpatRasters allows the calculation of factors such as slope within forests, and examine how slope position may impact forest structure. To calculate slope data is extracted from a Digital Terrain Model (DTM), which is a SpatRaster that contains topography data of a rectangular grid. The topographic data is used to calculate a Topographic Position Index and classify each polygon within 6 slope position variables:

- valley
- lower slope
- middle slope
- flat slope
- upper slope
- ridge.

The extracted slope metrics are then joined to the SpatVector to examine the effect of slope and fire severity from the 2019/20 wildfires on forest characteristics.

3.2.1 Slope position and fire severity affect mean tree height and canopy cover

Slope position is known to influence forest type and productivity due to soil conditions and moisture availability, which also influences fire behaviour. Figure 13 shows the trends in mean P95 CHM returns and canopy cover for each slope position and fire extent and severity mapping (FESM) category for three of the LiDAR capture areas. There is a general trend of lower tree top height and canopy cover as fire severity increases, combined with a trend of decreasing mean P95 CHM returns from the lower valley slope position to ridges.

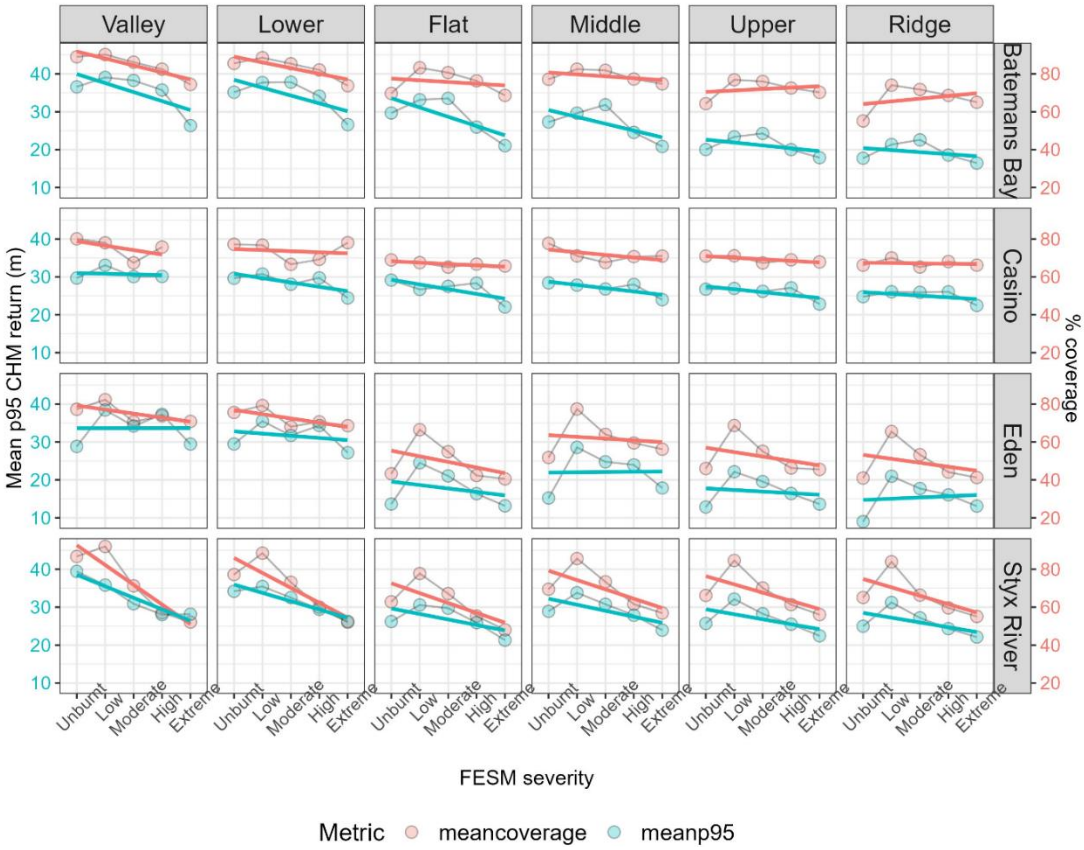

Figure 13 – Effect of slope position and fire severity on P95 CHM return and canopy cover

The same data is presented in Figure 14 to illustrate the effect of fire severity on mean top height and canopy cover.

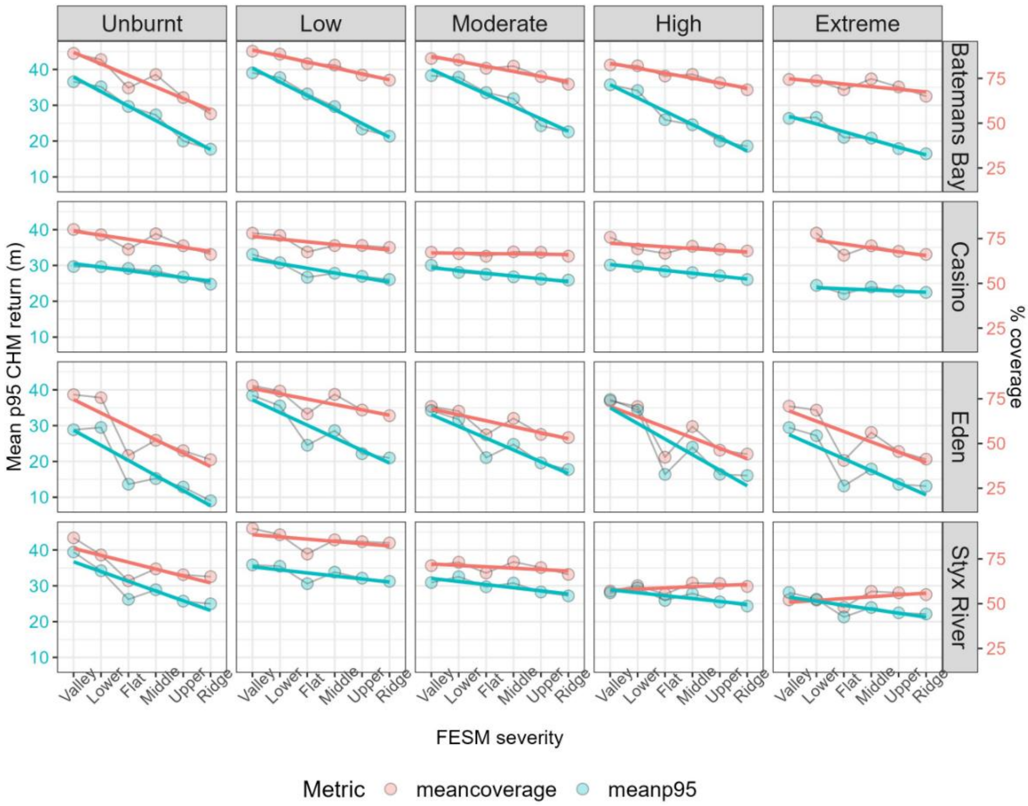

Figure 14 – P95 CHM returns and canopy cover by fire severity category

3.2.2 Tree height distribution illustrates mosaic of forest age classes

The distribution of P95 CHM returns can be extracted from LiDAR metrics to illustrate the variation across forests from the local to the landscape scale.

Figure 15 shows the P95 CHM returns distribution for one whole Local Landscape Area (LLA) within the Port Macquarie region ('Bottle Brush').

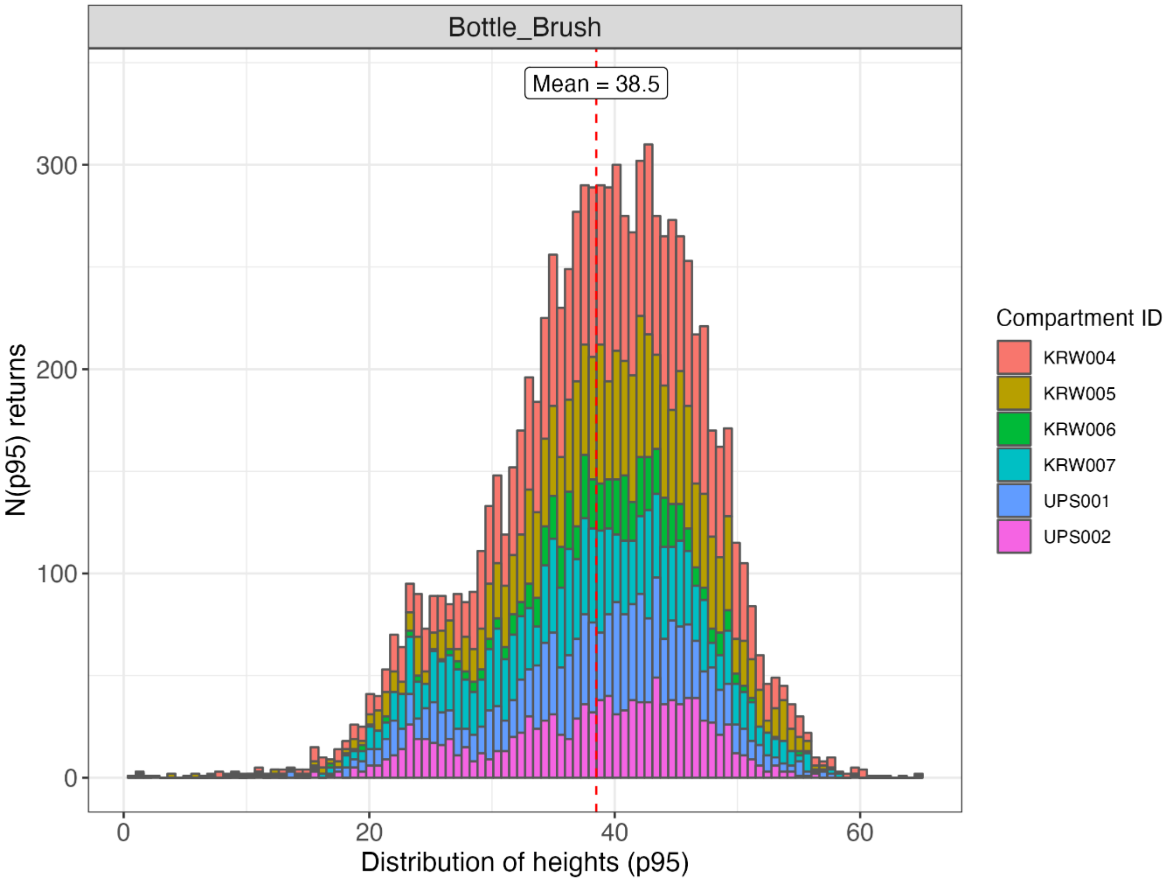

Figure 15 – Density of P95 CHM return by P95 CHM value for Bottle Brush Local Landscape Area coloured by compartment number

Figure 16 shows the distribution for each compartment within the same LLA.

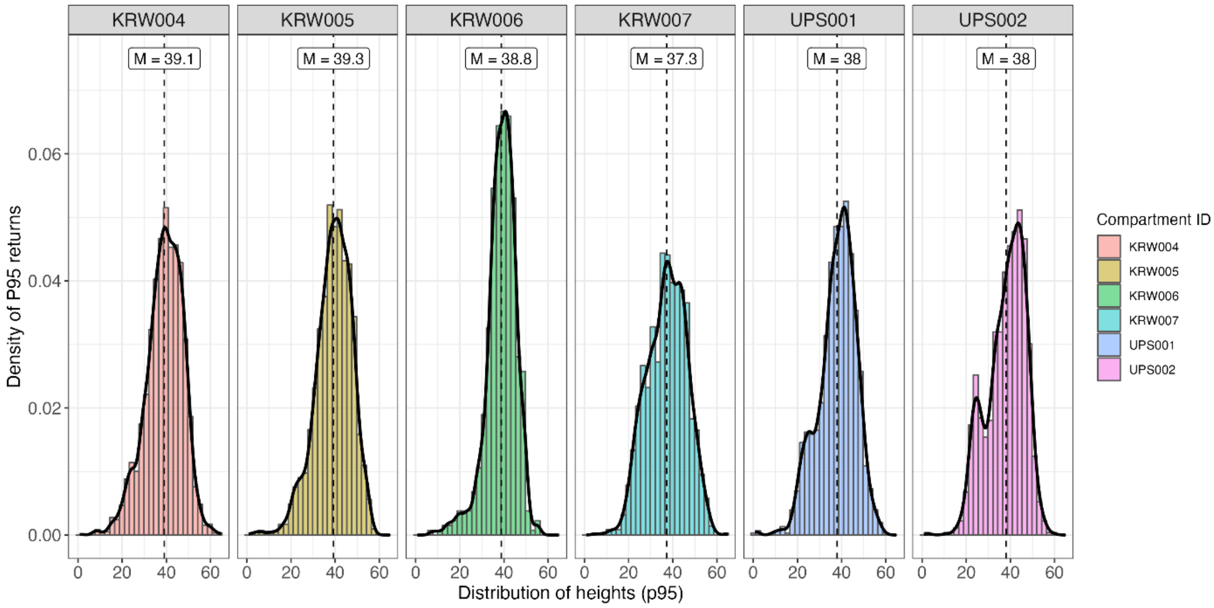

Figure 16 - Density of P95 CHM return by P95 CHM value for each compartment within the Bottle Brush Local Landscape Area

Return distribution can also be identified for common zones within forest management areas to differentiate between features excluded from harvesting to meet soil stability or biodiversity conservation goals, as illustrated in Figure 17.

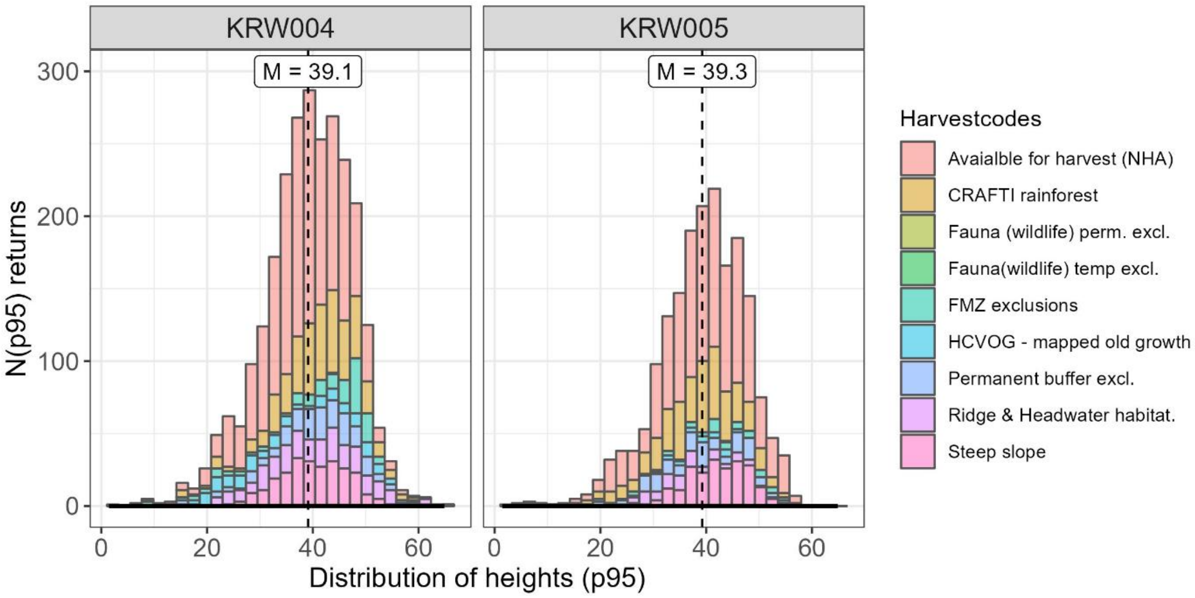

Figure 17 – Number of P95 CHM returns by P95 CHM value for trees within harvest exclusion zones in compartments KRW004 & KRW005 in the Bottle Brush LLA

The analysis can be repeated at any scale from Patch (approx. 10ha) to Compartment (approx. 300 to 500ha) to Local Landscape Area (approx. 1,500ha), with mean top height (p95) shown at each scale to show the mosaic across the forested area. This is illustrated in Figure 18 to Figure 21.

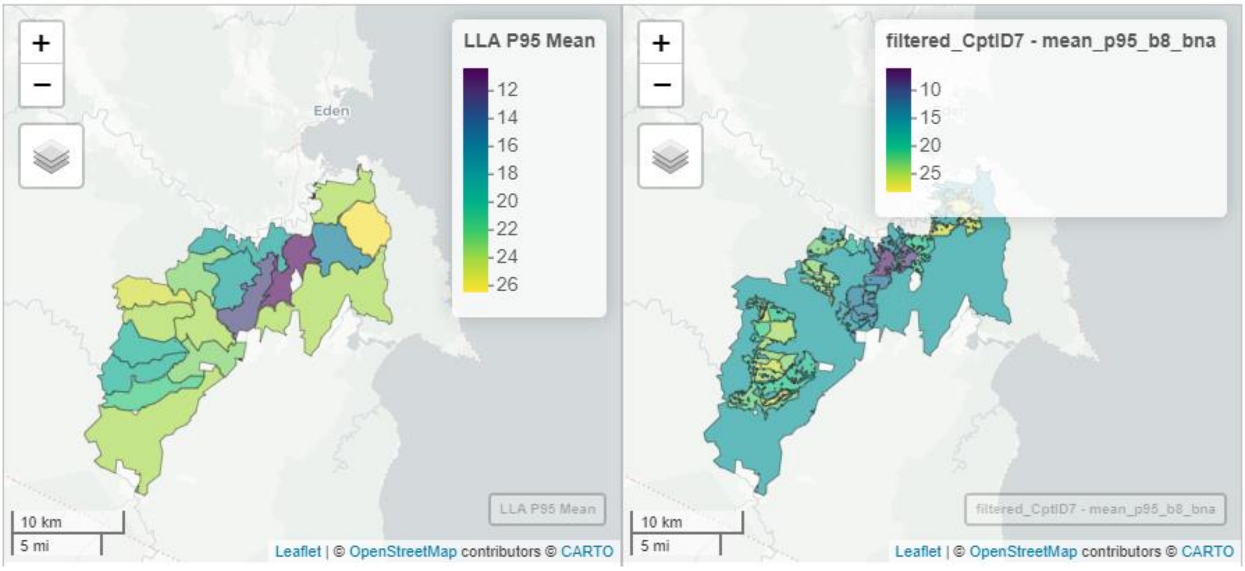

Figure 18 – Mean top height (p95) mosaic at the LLA scale (left) and for compartments within the Base Net Area (right) for the Eden LiDAR capture area

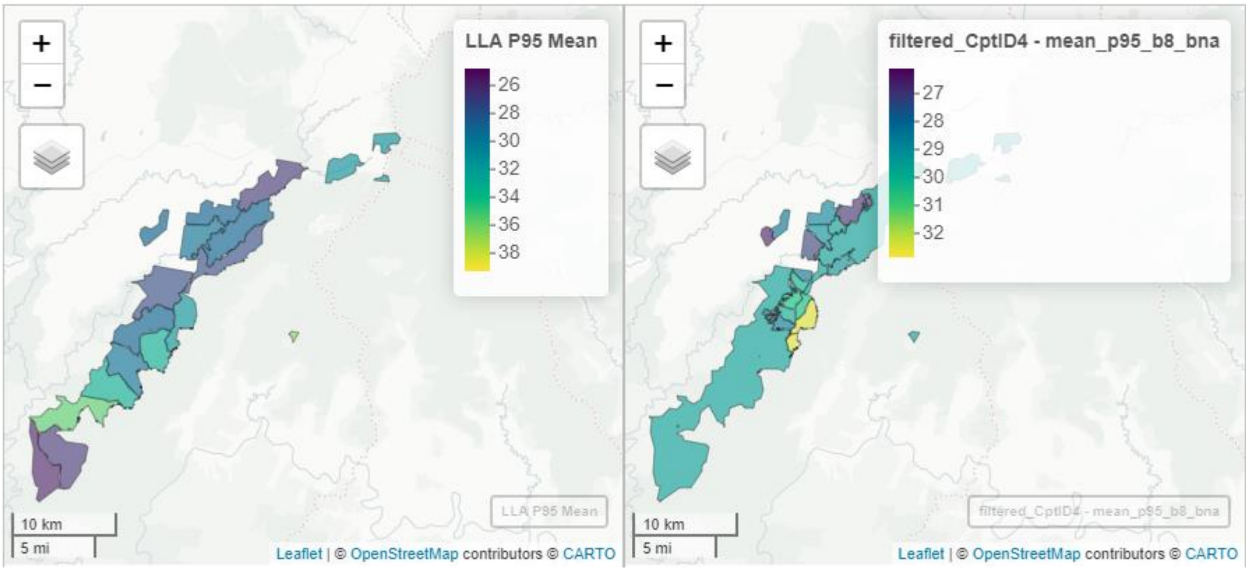

Figure 19 – Mean top height (p95) mosaic at the LLA scale (left) and for compartments within the Base Net Area (right) for the Styx River LiDAR capture area

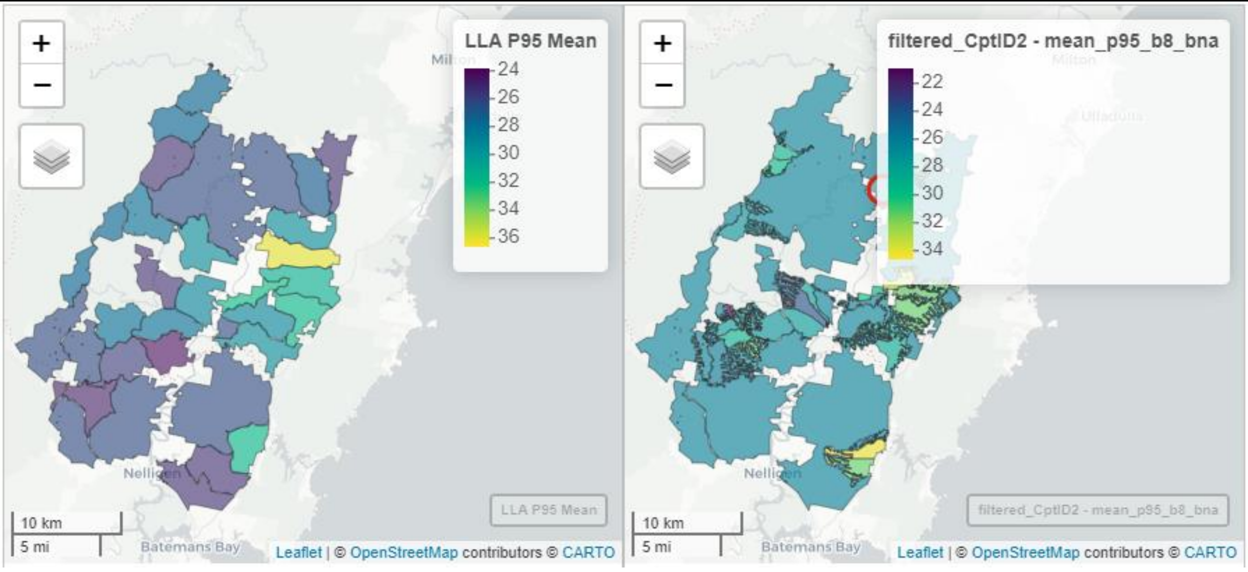

Figure 20 – Mean top height (p95) mosaic at the LLA scale (left) and for compartments within the Base Net Area (right) for the Batemans Bay LiDAR capture area

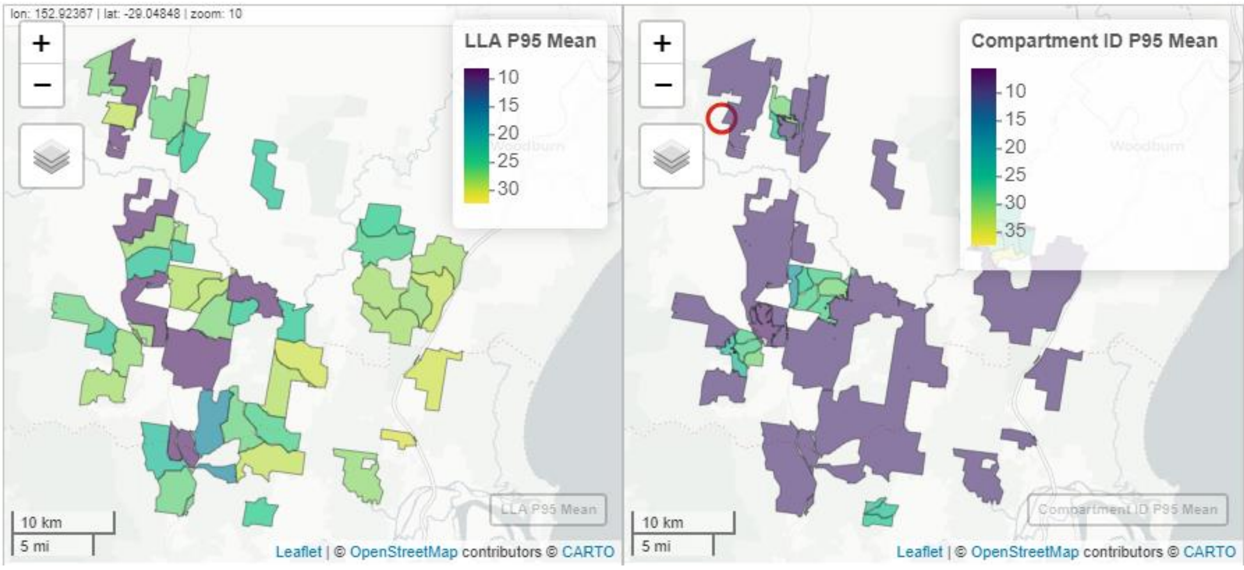

Figure 21 – Mean top height (p95) mosaic at the LLA scale (left) and for compartments within the Base Net Area (right) for the Casino LiDAR capture area

4 Conclusions

This report has presented the methods used to process and analyse recently acquired ALS data in a selection of State forests in NSW. The data provides a wealth of information with respect to forest structure across the landscape, including in areas where recent harvesting has taken place and areas affected by the 2019/20 wildfires.

4.1 Suitability of data and methods for monitoring impact of the Coastal IFOA on forest values

Airborne LiDAR data and spatial analysis can provide high-resolution information about forest structure and its relationship to topography, natural disturbances and forest management activities. This is particularly useful for monitoring temporal changes in forest structure, health and habitat diversity.

However, while airborne LiDAR provides a comprehensive characterisation of forest structure across the landscape, by itself it is somewhat limited in its ability to represent forest composition and function without the integration of additional information.

The analysis presented in this report has integrated LiDAR-derived metrics with spatial data for forest management boundaries, fire history and harvesting history to explore relationships and develop outputs that could be used to answer Coastal IFOA monitoring questions. Further analysis and interpretation of outputs is required to address specific monitoring questions.

4.2 Next steps

In line with the objectives of the Coastal IFOA monitoring program and the NSW Government commitment to open data the following will be implemented:

- Raw data and derived metrics will be made publicly available to enable other researchers to add to the body of knowledge and to support transparency in the assessment of impacts of forestry practices
- The analysis will be extended to include previous LiDAR data captures over the same areas and analyse change over time, including identifying drivers of change where data is available

4.4 Recommendations for further work

The ALS captured here is an extremely valuable resource which could be analysed further to gain other insights. In particular, integration with field data would allow models of target variables to be generated (e.g., aboveground biomass, tree species).

Recommendations for further work include:

- Integrate other spatial and non-spatial data (e.g. site quality, inventory plots, DPI 2018 feasibility study) into analysis
- Integrate LiDAR metrics into analysis of Coastal IFOA fauna monitoring results and species occupancy modelling, as well as input to research into habitat suitability under the koala research program
- Integrate LiDAR metrics with other field-based and remote sensing analysis of forest recovery following the 2019-2020 wildfires
- Further explore structural diversity within local landscape areas by integrating management and natural disturbance histories
- Further explore the effect of fire severity on structural characteristics of different forest types and landscape positions
- Explore how imputation methods could be used to extrapolate analysis across other state forest areas

5 References

Alberti, G. (2023). Landform package in R. 10.13140/RG.2.2.33628.36483/1.

Appelhans, T., Detsch, F., Reudenbach, C., & Woellauer, S. (2016, April). mapview-Interactive viewing of spatial data in R. In *EGU General Assembly Conference Abstracts* (pp. EPSC2016-1832).

Beier, P. and Noss, R.F. (1998). Do habitat corridors provide connectivity? *Conservation Biology*. 12: 1241-1252.

Cheng, J., Karambelkar, B., & Xie, Y. Leaflet: Create Interactive Web Maps with the JavaScript 'Leaflet'Library; R Package Version 2.0. 4.1. 2021.

Evans, J. S., & Ram, K. (2021). Package 'spatialEco'. *R CRAN Project*.

Hijmans RJ. 2023. terra: Spatial Data Analysis [Internet]. https://CRAN.R-project.org/package=terra

Hijmans, R. J., Van Etten, J., Mattiuzzi, M., Sumner, M., Greenberg, J. A., Lamigueiro, O. P., ... & Shortridge, A. (2013). Raster package in R. *Version. https://mirro rs. sjtug. sjtu. edu. cn/cran/web/packa ges/rast e r/raster. pdf*.

Khosravipour A, Skidmore AK, Isenburg M, Wang T, Hussin YA. 2014. Generating Pit-free Canopy Height Models from Airborne Lidar. Photogramm Eng Remote Sens. 80(9):863–872.

McDonald, R.C., Isbell, R. F., Speight, J.G., Walker, J. and Hopkins, M.S. (1984). *Australian soil and land survey. Field handbook*. Inkata, Melbourne. pp 165

Pebesma E, Bivand R (2023). *Spatial Data Science: With applications in R*. Chapman and Hall/CRC. doi:10.1201/9780429459016, https://r-spatial.org/book/.

Roussel J-R, Auty D, Coops NC, Tompalski P, Goodbody TRH, Meador AS, Bourdon J-F, de Boissieu F, Achim A. 2020. lidR: An R package for analysis of Airborne Laser Scanning (ALS) data. *Remote Sens Environ*. 251:112061.

Tennekes M (2018). "tmap: Thematic Maps in R." *Journal of Statistical Software*, **84**(6), 1–39. doi:10.18637/jss.v084.i06.

Tischendorf, L. and Fahrig, L. (2000). On the usage and measurement of landscape connectivity. *Oikos*. 90: 7-19.

Wickham H, Averick M, Bryan J, Chang W, McGowan LD, François R, Grolemund G, Hayes A, Henry L, Hester J, Kuhn M, Pedersen TL, Miller E, Bache SM, Müller K, Ooms J, Robinson D, Seidel DP, Spinu V, Takahashi K, Vaughan D, Wilke C, Woo K, Yutani H (2019). "Welcome to the tidyverse." *Journal of Open Source Software*, **4**(43), 1686. doi:10.21105/joss.01686.

Wickham, H., François, R., Henry, L., & Müller, K. (2018). dplyr: A Grammar of Data Manipulation. R package version 0.7. 6. *Computer software]. https://CRAN. R-project. org/package= dplyr*.

Appendix 1 – State forests within each LiDAR capture area

Capture Area	State Forest
Casino	Banyabba
	Braemar
	Bungawalbin
	Camira
	Carwong
	Devils Pulpit
	Doubleduke
	Ellangowan
	Gibberagee
	Mororo
	Myrtle
	Tabbimoble
	Whiporie
Coffs Harbour	Conglomerate
	Lower Bucca
	Orara East
	Wedding Bells
Styx River	Styx River
Bulahdelah	Bulahdelah
	Wang Wauk
Eden	East Boyd
	Timbillica

Capture Area	State Forest
Port Macquarie	Lansdowne
	Lorne
	Comboyne
	Upsalls Creek
	Kerewong
	North Branch
	Johns River
	Middle Brother
	Kew
	Kendall
	Broken Bago
	Burrawan
	Cowarra
	Cairncross
	Ballengarra
Batemans Bay	Benandarah
	Boyne
	Clyde
	Currowan
	Flat Rock
	Kioloa
	North Brooman
	South Brooman
	Shallow Crossing
	Yadboro

Appendix 2 – ALS processing steps in R

Airborne laser scanning (ALS) is increasingly used to create enhanced forest inventories and monitor forest structure.

Typically, the company that acquires the data supplies it as 3D point clouds which are split into tiles of (e.g., 1km by 1km) to aid processing.

This document outlines the steps taken to create a canopy height model (CHM) and a range of lidar 'metrics' from the point cloud data. The lidR package in R was used to process the data, but the steps are more-or-less comparable when using other lidar processing software (e.g., Lastools, Fusion).

Install and load the required packages:

```
library(lidR) # package for processing of las files
library(future) # allows multi-core processing
library(sf) # spatial features package, for working with vector-based
spatial data
library(terra) # a raster processing package
library(PerformanceAnalytics)
```

Set the working directory (or use relative path names):

```
# setwd(<directory where LAZ directory is located>)
indir <- 'LAZ' # directory name where las files are located
```

To get the boundaries of the las files (for use in a GIS) the following script can be used:

```
ctg <- readLAScatalog(indir) #read in the catalogue of las files
spx <- as.spatial(ctg) # convert catalogue boundaries to spatial layer
spx <- st_as_sf(spx) # convert sp object to sf object
st_crs(spx) <- 'EPSG:7856' # set projection if needed (GDA 2020 zone 56)
dir.create('shapes')

st_write(spx, 'shapes/lidar_boundaries.shp', append=FALSE) # write out as
shape file
```

Some tiles around the edges of the acquisition area contain too few points to adequately process, so we can remove (or move) files less than 50kb in size with the following code if required:

```
dir.create(paste0('LAZ/toosmall'))

x <- list.files(indir, pattern='las', full.names = T)

x <- x[sapply(x, file.size) < 50000]

file.rename(x, paste0('LAZ/toosmall/',basename(x)))
```

Height Normalisation

Height normalization replaces the Z (height) value for every point from an absolute measure (i.e., above sea level) to a relative measure from the ground. Therefore, in a forest the Z value will become the vegetation height above the ground.

The following code reads in a catalogue of las files, sets some processing options and then runs the normalize_height function from the lidR package.

```
ctg <- readLAScatalog(indir) # read in the catalogue

# Create directory for writing normalized files
outdir <- 'Normalized'
dir.create(outdir)

# Set some processing options
opt_output_files(ctg) <- paste0(outdir, "/{*}") # this writes out the files instead of holding them in memory
opt_laz_compression(ctg) <- TRUE # this writes out files as compressed laz files instead of las files
opt_filter(ctg) <- "-drop_class 7" # drop points classified as 'noise'
opt_chunk_buffer(ctg) <- 10 # change the buffer size if desired

# Using the future package, multi-core parameters are set (use plan(multisession, workers=n) to limit number of cores if problems with memory)
plan(multisession)

# The normalize function from the lidR is then called
normalize_height(ctg, tin())
```

The above can take many hours, depending on the size of the dataset and computer specifications. lidR automatically displays a handy progress plot.

Note that the 'TIN' method of height normalization is used here. A triangulated irregular network (TIN) triangulates between points to create a surface. Because we only want to triangulate between ground points, the point cloud needs to be classified prior to this function being run. The data from the supplier is usually already classified into basic classes (ground, vegetation, etc.)

It is important to note that each tile needs to be buffered to avoid edge effects between tiles (i.e., triangulation will use points from neighbouring tiles). Luckily, lidR creates on-the-fly buffers of 30 m by default. The buffer size can be modified if desired, using: e.g., opt_chunk_buffer(ctg) <- 10

If, for some reason, the processing fails and R crashes, the following code allows processed files to be flagged so they are not processed again. This will need to be inserted above after reading in the catalogue.

```
ctg2 <- readLAScatalog(outdir)
spctg2 <- as.spatial(ctg2)

ctg <- catalog_intersect(
   ctg,
   spctg2,
   subset = "flag_unprocessed"
 )
```

Canopy Height Model (CHM)

A CHM is a 2-dimensional representation of canopy height across the extent of lidar coverage. Many different algorithms have been proposed. The most simple, conceptually, is to place a grid with a cell size of, for example, 1m across the area and simply take the highest point in each cell. However, this can lead to canopy 'pits' and a poor quality output which looks speckled.

In the following code, the 'pit-free' algorithm of Khosravipour et al (2014) was used.

```
indir <- 'Normalized'

outdir <- 'Products/CHM'
dir.create('Products')

dir.create(outdir)

plan(multisession)

ctg <- readLAScatalog(indir) # as above, read in the catalogue, this time using the normalized files
opt_select(ctg) <- "xyz" # selecting only the xyz values of the points may use less memory
opt_output_files(ctg) <- paste0(outdir, "/{*}") # this will create individual output files for each tile. Only needed for large datasets, otherwise these are stored in memory and merged at the end.

# The function to create the CHM is as follows. This uses the pit-free algorithm, with specified height and edge parameters
chm <- rasterize_canopy(ctg, res = 1, algorithm = pitfree(thresholds = c(0, 10, 20, 30), max_edge = c(0, 1.5)), pkg = "terra")

z56 <- 'EPSG:7856' # GDA 2020 projection specification
crs(chm) <- z56 # set coordinate reference system

# The pit-free algorithm may still output a raster with some no-data pixels. The following function from the terra package fills any NA pixels with the mean of the surrounding pixels
chm <- focal(chm, w=3, fun='mean', na.rm=T, na.policy='only')

writeRaster(chm, 'Products/chm_1m.tif', overwrite=T) # write the output raster
```

LiDAR Metrics

LiDAR metrics are summary statistics of all of the points in a specified area. In the following, the Z values (height) are summarised across the landscape using a 30m grid. Therefore, in each 30 x 30 m cell, all the points in that cell are summarised into a single value (e.g., the 95th percentile, the mean, etc.)

```
# read in the catalogue of normalized point clouds and set some parameters
indir <- 'Normalized'
ctg <- readLAScatalog(indir)
opt_select(ctg) <- "xyz"
opt_filter(ctg) <- "-first_only" # filter the point cloud to only use first
returns

# This function calculates five common lidar metrics (cover, p95, average
height, standard deviation and skewness)
f = function(z)
 {
   cov = length(z[z>2])/length(z)*100
   q95 = quantile(z, 0.95)
   avg = mean(z)
   sd = sd(z)
   skew = PerformanceAnalytics::skewness(z)
   return(list(cov = cov, q95 = q95, avg = avg, sd = sd, skew = skew))
 }

plan(multisession)

# run the pixel_metrics function, using a 30 metre grid size
metrics = pixel_metrics(ctg, ~f(Z), 30)

# set the projection information
z56 <- 'EPSG:7856'
crs(metrics) <- z56

# write out the rasters as individual files
terra::writeRaster(metrics[[1]], 'Products/cov_firstOnly_30m.tif',
overwrite=T)
terra::writeRaster(metrics[[2]], 'Products/p95_firstOnly_30m.tif',
overwrite=T)
terra::writeRaster(metrics[[3]], 'Products/avg_firstOnly_30m.tif',
overwrite=T)
terra::writeRaster(metrics[[4]], 'Products/sd_firstOnly_30m.tif',
overwrite=T)
terra::writeRaster(metrics[[5]], 'Products/skewness_firstOnly_30m.tif',
overwrite=T)
```

Structural Index

The FCNSW structural index produces a surface representing structure across a broader landscape. The following code creates a custom ‘forest structure index’ from the 1m CHM:

```
chm <- rast('Products/chm_1m.tif') # load in the raster
chm <- chm*chm # square the CHM
chm <- terra::aggregate(chm, fact=5, fun='sum', na.rm=T) # aggregate to 5m cells, using the sum
structindex <- focal(chm, w=9, fun='sum') # create a focal sum using 9x9 cells surrounding each pixel

writeRaster(structindex, 'Products/structural_index_5m.tif', overwrite=T)
```

Calculating descriptive values from LiDAR metrics

The following R code was developed by the Zac Coates, Garston Liang, Augustine Nguyen, Johanna Voeste, Gavin Cooper and Scott Brown from the University of Newcastle to integrate LiDAR metrics with spatial data and generate insights about the relationship between forest structure, natural features and disturbance history.

```
#Load required packages

require(tidyverse)

require(sf)

require(terra)

require(dplyr)

#Load required data of multipolygon boundaries (vector)
boundaries_info <- st_layers("Data/DataExtraction.gdb")
boundaries <- list() ## To store all the boundaries, for different layers.
for (i in 1:length(boundaries_info$name)) {
  boundaries[[i]] <-
st_read("Data/DataExtraction.gdb",layer=boundaries_info$name[i])
}

#save names of boundaries
names(boundaries) <- boundaries_info$name

#fix geometry type of boundary (this may not be required for all boundaries)
somepolys <- boundaries [[1]]
somepolys <- st_cast(somepolys, "MULTIPOLYGON")
```

```
#load lidar data for extraction (raster)

somedatcasino <- terra::rast("metrics/Area1_Casino_avg_firstOnly_30m.tif")


#transform so crs (coordinate reference system) of vector and raster are the same

somepolys <- st_transform(somepolys, st_crs(somedatcasino))


#extract mean, standard deviation, and max from raster for each multipolygon

casinomean <- terra::extract(x=somedatcasino, y=somepolys, fun=mean)

casinosd <- terra::extract(x=somedatcasino, y=somepolys, fun=sd)

casinomax <- terra::extract(x=somedatcasino, y=somepolys, fun=max)


#bind extracted descriptive data back to vector data

somepolys <- cbind(casinomean, somepolys)


#Identify which raster capture data was extracted from

# vector of column names to check


columns_to_check <- c(2, 4, 6, 8, 10, 12, 14, 16)


# new column "capture_id" with NA values in your 'somepolys' dataframe
somepolys$capture_id_b1 <- NA


# loop through each row and check the specified columns


for (i in 1:nrow(somepolys)) {
  for (col in columns_to_check) {
    if (!is.na(somepolys[i, col])) {
      somepolys[i, "capture_id_b1"] <- (col - 1) %/% 2 + 1
      break
    }
  }
}


#clean up data converging data from all raster captures


# make replacement columns list
replacement_column_numbers <- c(4, 6, 8, 10, 12, 14,16)
main_column_number <- 2  # should be avg column
```

```
#replace the columns putting data into main column

for (replacement_col_num in replacement_column_numbers) {
  na_rows <- is.na(somepolys[[main_column_number]])
  somepolys[[main_column_number]][na_rows] <-
somepolys[[replacement_col_num]][na_rows]
}


# delete purposeless columns

somepolys <- somepolys[, -replacement_column_numbers]


# delete other purposelesscolumns

columns_to_remove <- c("ID.1", "ID.2", "ID.3", "ID.4", "ID.5", "ID.6",
"ID.7")


# resave back to somepolys

somepolys <- somepolys[, !colnames(somepolys) %in% columns_to_remove]


#rename avg column in somepolys to mean (repeat steps for sd and max)

somepolys <- somepolys %>%
  rename(mean_avg_b1_landunits = avg)


#join mean, sd and max data

somepolysleftjoin <- left_join(somepolys, select(somepolysd,
sd_avg_b1_landunits, ID), by = "ID")
somepolysleftjoin <- left_join(somepolysleftjoin, select(somepolymax,
max_avg_b1_landunits, ID), by = "ID")
b1_landunits_avg <- somepolysleftjoin



#save data frame for each lidar metric to join
save(b1_landunits_avg,file="dataframes/b1_landunits_avg.rds")


#this process should be looped for all 8 capture zones and any multipolygon
boundaries


#load each spatial data frame (vector data)
load("dataframes/b1_landunits_avg.rds")
load("dataframes/b1_landunits_cov.rds")
load("dataframes/b1_landunits_p95.rds")
```

```
load("dataframes/b1_landunits_sd.rds")
load("dataframes/b1_landunits_skew.rds")
load("dataframes/b1_landunits_structural_index.rds")


#join each spatial data frame


b1_landunits <- left_join(b1_landunits_avg, select(b1_landunits_cov,
mean_cov_b1_landunits, sd_cov_b1_landunits, max_cov_b1_landunits, ID), by =
"ID")
b1_landunits <- left_join(b1_landunits, select(b1_landunits_p95,
mean_p95_b1_landunits, sd_p95_b1_landunits, max_p95_b1_landunits, ID), by =
"ID")
b1_landunits <- left_join(b1_landunits, select(b1_landunits_sd,
mean_sd_b1_landunits, sd_sd_b1_landunits, max_sd_b1_landunits, ID), by =
"ID")
b1_landunits <- left_join(b1_landunits, select(b1_landunits_skew,
mean_skew_b1_landunits, sd_skew_b1_landunits, max_skew_b1_landunits, ID),
by = "ID")
b1_landunits <- left_join(b1_landunits,
select(b1_landunits_structural_index, mean_focal_sum_b1_landunits,
sd_focal_sum_b1_landunits, max_focal_sum_b1_landunits, ID), by = "ID")


#identify which boundary data is from (useful for when all data is joined)
b1_landunits$b1 <- 1


#reasign data “spatial” class


b1_landunits <- b1_landunits %>% st_as_sf()


#save data for all boundary join
save(b1_landunits,file="dataframes/b1_landunits.rds")


#load all boundary data


load("dataframes/b1_landunits.rds")
load("dataframes/b2_harvestplanareagross.rds")
load("dataframes/b3_patches.rds")
load("dataframes/b4_whc.rds")
load("dataframes/b5_trc.rds")
load("dataframes/b6_treecoastal.rds")
load("dataframes/b7_fesm.rds")
load("dataframes/b8_bna.rds")
load("dataframes/b9_harvesthistory.rds")


#join data together based on spatial shape and location (join by largest to
resolve duplication of data)
```

```
bna_treecoastal <- st_join(b8_bna, b6_treecoastal, largest=TRUE)
bna_treecoastal_fesm <- st_join(bna_treecoastal, b7_fesm, largest=TRUE)
bna_treecoastal_fesm_harvesthistory <- st_join(bna_treecoastal_fesm,
b9_harvesthistory, largest=TRUE)
bna_treecoastal_fesm_harvesthistory_patches <-
st_join(bna_treecoastal_fesm_harvesthistory, b3_patches, largest=TRUE)
bna_treecoastal_fesm_harvesthistory_patches_landunits <-
st_join(bna_treecoastal_fesm_harvesthistory_patches, b1_landunits,
largest=TRUE)
bna_treecoastal_fesm_harvesthistory_patches_landunits_trc <-
st_join(bna_treecoastal_fesm_harvesthistory_patches_landunits, b5_trc,
largest=TRUE)
bna_treecoastal_fesm_harvesthistory_patches_landunits_trc_whc <-
st_join(bna_treecoastal_fesm_harvesthistory_patches_landunits_trc, b4_whc,
largest=TRUE)
b8_b6_b7_b9_b3_b1_b5_b4_b2 <-
st_join(bna_treecoastal_fesm_harvesthistory_patches_landunits_trc_whc,
b2_harvestplanareagross, largest=TRUE)


#save data frame

save(b8_b6_b7_b9_b3_b1_b5_b4_b2,
file="dataframes/b8_b6_b7_b9_b3_b1_b5_b4_b2.rds")
```

Appendix 3 – Spatial data files used in analysis

Description	Filename	File type
Casino first returns average value, 30m resolution	Area1_Casino_avg_firstOnly_30m.tif	Tagged Image File (.tif)
Casino first returns 95th percentile, 30m resolution	Area1_Casino_p95_firstOnly_30m.tif	Tagged Image File (.tif)
Casino digital terrain model, 30m resolution	Area1_Casino_dtm_30m.tif	Tagged Image File (.tif)
Casino first returns coverage value, 30m resolution	Area1_Casino_cov_firstOnly_30m.tif	Tagged Image File (.tif)
Casino first returns standard deviation, 30m resolution	Area1_Casino_sd_firstOnly_30m.tif	Tagged Image File (.tif)
Casino first returns skewness, 30m resolution	Area1_Casino_skewness_firstOnly_30m.tif	Tagged Image File (.tif)
Casino structural index, 30m resolution	Area1_Casino_structural_index_30m.tif	Tagged Image File (.tif)
Coffs Harbour first returns average value, 30m resolution	Area2_Coffs_Harbour_avg_firstOnly_30m.tif	Tagged Image File (.tif)
Coffs Harbour first returns 95th percentile, 30m resolution	Area2_Coffs_Harbour_p95_firstOnly_30m.tif	Tagged Image File (.tif)
Coffs Harbour digital terrain model, 30m resolution	Area2_Coffs_Harbour_dtm_30m.tif	Tagged Image File (.tif)
Coffs Harbour first returns coverage value, 30m resolution	Area2_Coffs_Harbour_cov_firstOnly_30m.tif	Tagged Image File (.tif)
Coffs Harbour first returns standard deviation, 30m resolution	Area2_Coffs_Harbour_sd_firstOnly_30m.tif	Tagged Image File (.tif)
Coffs Harbour first returns skewness, 30m resolution	Area2_Coffs_Harbour_skewness_firstOnly_30m.tif	Tagged Image File (.tif)
Coffs Harbour structural index, 30m resolution	Area2_Coffs_Harbour_structural_index_30m.tif	Tagged Image File (.tif)
Armidale first returns average value, 30m resolution	Area3_Armidale_avg_firstOnly_30m.tif	Tagged Image File (.tif)
Armidale first returns 95th percentile, 30m resolution	Area3_Armidale_p95_firstOnly_30m.tif	Tagged Image File (.tif)
Armidale digital terrain model, 30m resolution	Area3_Armidale_dtm_30m.tif	Tagged Image File (.tif)
Armidale first returns coverage value, 30m resolution	Area3_Armidale_cov_firstOnly_30m.tif	Tagged Image File (.tif)
Armidale first returns standard deviation, 30m resolution	Area3_Armidale_sd_firstOnly_30m.tif	Tagged Image File (.tif)
Armidale first returns skewness, 30m resolution	Area3_Armidale_skewness_firstOnly_30m.tif	Tagged Image File (.tif)
Armidale structural index, 30m resolution	Area3_Armidale_structural_index_30m.tif	Tagged Image File (.tif)

Description	Filename	File type
Bulahdelah first returns average value, 30m resolution	Area4_Bulahdelah_avg_firstOnly_30m.tif	Tagged Image File (.tif)
Bulahdelah first returns 95th percentile, 30m resolution	Area4_Bulahdelah_p95_firstOnly_30m.tif	Tagged Image File (.tif)
Bulahdelah digital terrain model, 30m resolution	Area4_Bulahdelah_dtm_30m.tif	Tagged Image File (.tif)
Bulahdelah first returns coverage value, 30m resolution	Area4_Bulahdelah_cov_firstOnly_30m.tif	Tagged Image File (.tif)
Bulahdelah first returns standard deviation, 30m resolution	Area4_Bulahdelah_sd_firstOnly_30m.tif	Tagged Image File (.tif)
Bulahdelah first returns skewness, 30m resolution	Area4_Bulahdelah_skewness_firstOnly_30m.tif	Tagged Image File (.tif)
Bulahdelah structural index, 30m resolution	Area4_Bulahdelah_structural_index_30m.tif	Tagged Image File (.tif)
Wauchope first returns average value, 30m resolution	Area5_Wauchope_avg_firstOnly_30m.tif	Tagged Image File (.tif)
Wauchope first returns 95th percentile, 30m resolution	Area5_Wauchope_p95_firstOnly_30m.tif	Tagged Image File (.tif)
Wauchope digital terrain model, 30m resolution	Area5_Wauchope_dtm_30m.tif	Tagged Image File (.tif)
Wauchope first returns coverage value, 30m resolution	Area5_Wauchope_cov_firstOnly_30m.tif	Tagged Image File (.tif)
Wauchope first returns standard deviation, 30m resolution	Area5_Wauchope_sd_firstOnly_30m.tif	Tagged Image File (.tif)
Wauchope first returns skewness, 30m resolution	Area5_Wauchope_skewness_firstOnly_30m.tif	Tagged Image File (.tif)
Wauchope structural index, 30m resolution	Area5_Wauchope_structural_index_30m.tif	Tagged Image File (.tif)
Merimbula first returns average value, 30m resolution	Area6_Merimbula_avg_firstOnly_30m.tif	Tagged Image File (.tif)
Merimbula first returns 95th percentile, 30m resolution	Area6_Merimbula_p95_firstOnly_30m.tif	Tagged Image File (.tif)
Merimbula digital terrain model, 30m resolution	Area6_Merimbula_dtm_30m.tif	Tagged Image File (.tif)
Merimbula first returns coverage value, 30m resolution	Area6_Merimbula_cov_firstOnly_30m.tif	Tagged Image File (.tif)
Merimbula first returns standard deviation, 30m resolution	Area6_Merimbula_sd_firstOnly_30m.tif	Tagged Image File (.tif)
Merimbula first returns skewness, 30m resolution	Area6_Merimbula_skewness_firstOnly_30m.tif	Tagged Image File (.tif)
Merimbula structural index, 30m resolution	Area6_Merimbula_structural_index_30m.tif	Tagged Image File (.tif)
Port Macquarie first returns average value, 30m resolution	Area7_Port_Maquarie_avg_firstOnly_30m.tif	Tagged Image File (.tif)
Port Macquarie first returns 95th percentile, 30m resolution	Area7_Port_Maquarie_p95_firstOnly_30m.tif	Tagged Image File (.tif)

Description	Filename	File type
Port Macquarie digital terrain model, 30m resolution	Area7_Port_Maquarie_dtm_30m.tif	Tagged Image File (.tif)
Port Macquarie first returns coverage value, 30m resolution	Area7_Port_Maquarie_cov_firstOnly_30m.tif	Tagged Image File (.tif)
Port Macquarie first returns standard deviation, 30m resolution	Area7_Port_Maquarie_sd_firstOnly_30m.tif	Tagged Image File (.tif)
Port Macquarie first returns skewness, 30m resolution	Area7_Port_Maquarie_skewness_firstOnly_30m.tif	Tagged Image File (.tif)
Port Macquarie structural index, 30m resolution	Area7_Port_Maquarie_structural_index_30m.tif	Tagged Image File (.tif)
Moruya first returns average value, 30m resolution	Area8_Moruya_avg_firstOnly_30m.tif	Tagged Image File (.tif)
Moruya first returns 95th percentile, 30m resolution	Area8_Moruya_p95_firstOnly_30m.tif	Tagged Image File (.tif)
Moruya digital terrain model, 30m resolution	Area8_Moruya_dtm_30m.tif	Tagged Image File (.tif)
Moruya first returns coverage value, 30m resolution	Area8_Moruya_cov_firstOnly_30m.tif	Tagged Image File (.tif)
Moruya first returns standard deviation, 30m resolution	Area8_Moruya_sd_firstOnly_30m.tif	Tagged Image File (.tif)
Moruya first returns skewness, 30m resolution	Area8_Moruya_skewness_firstOnly_30m.tif	Tagged Image File (.tif)
Data storage model from ArcGis, stores shape data for various forest layers	DataExtraction.gbd	Geodatabase (.gbd)
Data storage model from ArcGis, stores shape data for forest harvest history	HarvestHistoryPancakes.gbd	Geodatabase (.gbd)