

Article

Possibilities and Limitations of a Geospatial Approach to Refine Habitat Mapping for Greater Gliders (*Petauroides* spp.)

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Abstract: Hollow-dependent wildlife has been declining globally due to the removal of hollow-bearing trees, yet these trees are often unaccounted for in habitat mapping. As on-ground field surveys are costly and time-consuming, we aimed to develop a simple, accessible and transferrable geospatial approach using freely accessible LiDAR to refine habitat mapping by identifying high densities of potential hollow-bearing trees. We assessed if LiDAR from 2009 could be accurately used to detect tree heights, which would correlate to tree diameter at breast height (DBH), which in turn would identify trees that are more likely to be hollow-bearing. Here, we use habitat mapping of greater gliders (*Petauroides* spp.) in the Fraser Coast region of Australia as a case study. Across four sites, field surveys were conducted in 2023 to assess the tree height and density of large trees (>50 cm DBH per 1 km²) at 19 transects (n = 91). This was compared to outputs from individual tree detection derived from unsupervised classification using a local maximal filter and variable window size to identify treetops in freely available LiDAR. Tree height was measured with an accuracy of RMSE 5.75 m, and we were able to identify transects with large trees (>50 cm DBH), which were more likely hollow bearing. However, there was no statistical evidence to suggest that transects with a high density of large trees could be accurately identified based on LiDAR alone (>50 cm DBH *p* 0.2298). Despite this, we have demonstrated that freely accessible LiDAR and unsupervised machine learning techniques can be utilised to identify large, potentially hollow-bearing trees on a broad scale to refine habitat mapping for hollow-dependent species. It is important to develop geospatial analysis methods that are more accessible to land managers, as deep machine learning methods and current LiDAR can be computationally intensive and expensive. We propose a workflow using free and accessible geospatial analysis methods to identify large, potentially hollow-bearing trees and determine how to address some limitations in this geospatial approach.

Keywords: hollow-bearing tree; geospatial analysis; hollow-dependent; greater glider; lidar



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1. Introduction

Old-growth forests are rapidly declining globally, with ~77% of Australian old-growth forests being logged or disturbed by fire over the last 25 years since 2020 [1,2]. This has been driven by the effects of climate change, increased fire frequency and severity [3] and land use changes, which result in logging and land clearing [4]. Old-growth forests are complex and highly productive areas that provide critical habitats and support the survival

and reproductive success of countless endangered and vulnerable species [1]. The removal and degradation of old-growth forests also come with the loss of key habitat features such as hollow-bearing trees [1,2]. Hollows are typically found in large old trees and are likely to be caused by fire, wind, termites, fungi and hollow-excavating vertebrates [5]. However, in areas that lack hollow excavators, such as Australia, hollow formation can take centuries [6]. The loss of hollow-bearing trees is predominately driven by native timber harvesting, frequent intense wildfires and land clearing, which often removes potential hollow-bearing trees before hollows can be established [7]. Thus, a lack of hollow-bearing trees has negatively impacted many Australian hollow-dependent species [1,2,8]. The conservation of endangered species often relies on the ability to accurately map and quantify areas of critical habitat [9]. Therefore, to conserve hollow-dependent wildlife, we must first identify areas likely to have hollow-bearing trees. However, the use of traditional on-ground field survey techniques proves a costly and time-consuming way to efficiently map and quantify habitat at broad spatial extents [10]. In comparison, geospatial analysis is an increasingly powerful tool for the fields of ecology and conservation [11,12] because it can provide a highly accurate alternative to traditional field surveys to more effectively map landscape variation [13]. This makes it an ideal tool to help prioritise decision-making for conservation outcomes at regional and landscape scales [14]. Geospatial analysis combines geographical information systems with remote sensing techniques to increase the accessibility for ecological surveys at vast spatial and temporal scales and resolutions [15,16].

Light Detection and Ranging (LiDAR) is one such remote sensing technology that generates a point cloud of an area by calculating the distance between a sensor and a target via laser [11,17]. For landscape or regional-scale surveys, commonly aerial laser scanning is used, where the LiDAR sensor is attached to a moving aircraft to cover large spatial extents [17]. Aircraft used to collect LiDAR are often either fixed-wing planes or unmanned aerial vehicles (UAVs), such as drones [17]. This approach generates large volumes of data in comparison to time-consuming on-ground field survey methods [18]. Open-access LiDAR data are becoming readily available and more frequently used to map habitats at large spatial scales, which can significantly decrease the high costs usually associated with geospatial and computational requirements [19]. LiDAR-derived point clouds are commonly used to build elevation models to visualise landscape structures [20], which can then be used in conjunction with geospatial analysis techniques to quantify forest metrics such as canopy height and density [21].

Many geospatial analysis techniques utilise machine learning to improve the mapping and understanding of forest features and structures by recognising hard-to-detect patterns within complex datasets [22,23]. Supervised machine learning uses a training dataset with predetermined and correct output values to accurately classify or predict model outcomes, whereas unsupervised machine learning uses human intervention to validate output results [24]. An example of this approach is the local maxima algorithm used in forestry to determine high points within a LiDAR point cloud, which are interpreted as the treetops; however, the results must be validated through on-ground surveys to avoid inaccurate results [25]. On the other hand, deep learning is a more advanced form of supervised learning based on artificial neural networks constructed by multiple layers to 'learn' from and optimise models [26]. However, this makes it significantly more computationally intensive and time-consuming, as it relies on large volumes of high-quality training/testing data [26]. Although unsupervised learning can have a higher risk of producing inaccurate results due to the lack of human intervention, this approach is faster and requires less technical expertise when working with large amounts of data [22,27]. Unsupervised machine learning, therefore, has the potential to be more accessible and can

be used to identify areas of large, likely hollow-bearing trees across broad extents to create an accessible and replicable method to refine areas of key habitat attributes.

The classification of vertical forest structure over a broad scale is a clear advantage of aerial LiDAR [28,29], unmatched by conventional survey methods [30]. Mapping vertical forest structure significantly increases the ability to assess potential habitat suitability and distribution of vulnerable animal species [31]. Analysis of vertical forest structure can identify and refine mapping for key structures within old-growth forest [32], such as potential hollow-bearing trees [33,34]. Previous studies have used geospatial analysis to identify potential hollow-bearing trees in Australian landscapes. For example, ref. [35] used LiDAR to identify trees in the later stages of senescence, which were more likely hollow bearing. They were able to successfully use LiDAR to identify key predictor variables of hollow presence, such as tree senescence class and crown form using remote data, to infer the location of potentially hollow-bearing trees. The authors of [36] used LiDAR and machine learning techniques with a variable window size to identify dead trees within stands of Eucalyptus forests that were more likely to possess hollows. They found that for Australian landscapes, the use of a variable window size was advantageous when identifying dead trees from live trees amongst the heterogeneous landscape.

Hollow-dwelling wildlife are often more susceptible to habitat loss because suitable hollow-bearing habitat trees can take centuries to form, coupled with rapid rates of habitat loss [37–39]. However, to better inform conservation outcomes for threatened hollow-dependent wildlife, we must identify areas of potential hollow-bearing trees. Unfortunately, there is a lack of management tools (such as GIS layers) to differentiate between old-growth forests, which contain hollow-bearing trees, and logged forests, which have few remaining habitat trees [1]. Therefore, there is a clear need to develop accessible, cost-effective and transferable methods to map vertical forest structure, which can be applied across a broad landscape for various applications [40]. Therefore, in this study, we aim to develop an accessible and easily replicable geospatial approach to refine habitat mapping by identifying potential hollow-bearing trees to better inform conservation outcomes for hollow-dependent species. Here, we use greater glider habitat mapping for the Fraser Coast region of Australia as an example.

The greater gliders (*Petauroides* spp.) are one threatened taxon that has been negatively affected by the detrimental loss of habitat trees and old-growth forests across Eastern Australia [38,41]. There are three different species of greater gliders: northern (*Petauroides minor*), central (*Petauroides armillatus*), and southern (*Petauroides volans*) [8]. Greater gliders utilise large hollows with entrances 7 to 12 cm in diameter [42], which are often formed in trees over 30 cm diameter at breast height (DBH), increasing in probability of occurrence with increasing tree size [39,43]. Greater gliders are particularly sensitive to changes in temperature and water availability; thus, climate change and wildfires are a major threat, in addition to habitat destruction [39]. In 2022, the conservation status of the central (*P. armillatus*) and southern (*P. volans*) greater gliders was upgraded to endangered [44], and consequently, following the impacts of the megafires of 2020, which devastated parts of Southeast Queensland, there is concern for the status of populations in this region. The upgraded conservation status of these species further highlights the importance of the conservation and management of large habitat trees Australia-wide.

The current habitat suitability mapping across Queensland, Australia, for greater gliders is based on verified species presence records, expert opinion and suitable regional ecosystem types, which are identified after analysing environmental conditions and dominant feed and den tree species [8]. A key limitation of high-quality habitat identified in the current mapping is that it does not consider or address the effect of vertical forest structure on the suitability of habitat for greater gliders, particularly regarding large, old-

growth forests that are more likely to contain suitable hollows. This has resulted in the current habitat mapping being too broad to effectively inform conservation decisions for the species.

In order to address the aim of our study, we test the hypothesis that areas of high density of potential hollow-bearing trees can be readily identified using a simple geospatial analysis approach by classifying vertical forest structure to refine habitat mapping for greater gliders of the Fraser Coast region of Australia. To assess if we could use geospatial analysis to identify potential hollow-bearing trees, we tested the following three assumptions: (1) LiDAR from 2009 can be used to accurately determine tree height, (2) tree height correlates to tree diameter when considering ecosystem type, and (3) tree diameter correlates to hollow presence.

2. Methods

2.1. Data Collection

To assess our hypothesis and test the three assumptions of our study, we first surveyed locations across the Fraser Coast, Queensland, and assessed various forest metrics, including tree height, diameter and hollow presence. This field data were compared against LiDAR data collected by the Queensland Government for the Fraser Coast Project in 2009 [15]. This LiDAR was used as it was the most up-to-date, freely available data for the region, which allowed us to test the application and efficacy of inexpensive LiDAR to refine habitat mapping, as old-growth trees are often senescent and do not rapidly increase in height within 10–15 years [43]. To assess our first assumption, using the point cloud data, we extracted tree height and compared the accuracy against the field survey data. We later assessed the correlation between tree height and diameter, considering ecosystem type to assess the second assumption, and finally, we tested if tree diameter correlates to hollow presence to assess the third assumption of this study. We then tested if LiDAR from 2009 could correctly identify sites with a high density of potentially hollow-bearing trees when compared against field survey data.

2.2. Field Surveys

Surveys were all conducted within the extent of current high-quality greater glider habitat mapping and freely accessible LiDAR from 2009 in order to assess the accuracy of older LiDAR for refining greater glider habitat mapping [45] (Figure 1). In February of 2023, four sites (two state-managed forests and two private properties) were selected because they were within the extent of current habitat mapping, had freely available LiDAR from 2009 and were accessible by road or track. Based on a summary of tracking studies for Southeast Queensland by [8], all sites featured preferred tree species for greater gliders: *Eucalyptus tereticornis* and *Eucalyptus latissinensis* (known preferred den tree species) and *Corymbia intermedia* (known feed tree species). The two private properties were periodically burnt using cool burns aimed at clearing excess dry undergrowth to diminish fuel loads for potential wildfires (Figure A1). Property A was burnt every 3–4 years, and Property B every 6 years, after purchasing the property in 2009. Property B was also selectively logged in the 1980s, predominantly for *Eucalyptus tereticornis* and *Lophostomen* sp., leaving only bifurcated and bent trees. Property A remains mostly remnant vegetation; however, parts of the property were cleared for grazing. Historically, the Fraser Coast region has undergone extensive logging from the time of European settlement [46]. Although we did not have access to recent logging history for either state forest, the current code of practice for native timber harvesting in Southeast Queensland state forests outlines that within high-quality greater glider habitats, a minimum of six live habitat trees and two recruitment trees must be retained throughout the harvesting area [47]. In order to be classified as a habitat tree,

the tree must be a dominant or co-dominant species within the regional ecosystem, with at least one hollow more than 10 cm in diameter [47]. Parts of Bauple State Forest, including the surveyed transects, were burnt in 2021 during a planned burn scheduled by Queensland Parks and Wildlife Service; however, the intensity of the burn is unknown. There was also active logging in parts of Bauple State Forest at the time of surveys but not within surveyed transects.

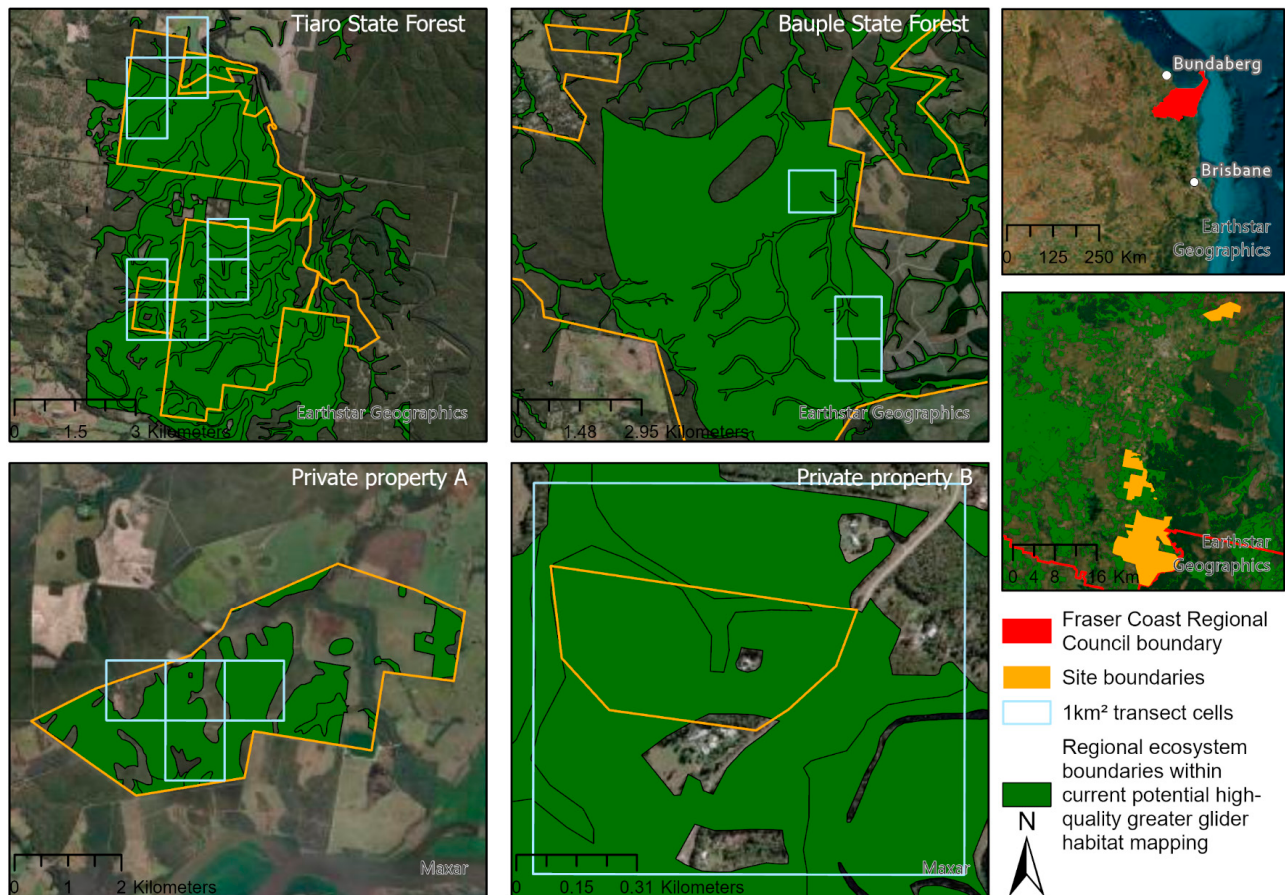


Figure 1. Map of each study site, including the extent of regional ecosystems within current high-quality greater glider habitat mapping. Each site displays the 1 km² cells in which at least one DBH belt transect and tree height survey were conducted.

After a preliminary analysis of tree height to identify expected density of large trees (>50 cm DBH) across the sites, nineteen 2000 m² (100 × 20 m) belt transects were conducted across the four sites, and DBH and hollow presence were recorded for each tree over 30 cm DBH ($n = 326$). Trees were surveyed if they were over 30 cm DBH, as that is the minimum DBH utilised by greater gliders [8]. Tree DBH was measured approximately 1.3 m from the ground. Hollow presence was recorded by one person so as to maintain consistency and was measured as >1 cm, where the entrance diameter is less than the depth of the hollow [48]. Trees of this size are often used as foraging trees and have the potential to be future den trees, while larger trees (>50 cm DBH) are utilised predominately as den trees [8]. A subset of approximately five trees at each site was also measured for tree height using a Nikon Laser Forestry Pro II rangefinder (Nikon, Tokyo, Japan) to measure height of trees with a clear view of the base and canopy ($n = 91$) to assess the accuracy of LiDAR tree height detection. The density of large trees per site (>50 cm DBH per 1 km²) was extrapolated from each transect.

2.3. Geospatial Analysis

We compared field measurements to tree heights extracted from 2009 LiDAR for each 1 km² cell that contained a belt transect. LiDAR elevation data, collected in 2009, was downloaded from Elvis—Elevation and Depth to cover the extent of each of the survey sites [45]. Although the LiDAR data used was from 2009, this was the most recent, freely available data at the time of this study. Therefore, inaccuracies would be expected; however, we aim to be able to utilise freely available LiDAR and accessible geospatial analysis methods to refine broad habitat mapping. The LiDAR point cloud data have a vertical accuracy of 0.15 m, and an average of 2 points per square metre was acquired using aerial laser scanning from a fixed-wing aircraft, collecting all returns within our study sites surveyed between July and September of 2009.

These data were used to individually detect treetop locations and extract tree heights for each study site, which were used to test the assumption that LiDAR could accurately determine tree heights. The lidR package version 4.0.3 was used for the LiDAR data processing [49,50], following the general workflow by [50]. Due to the large extent of the study sites, data were processed in a batch format for each transect cell so that the 1 km² tiles were run consecutively for an entire site before being combined into one output (Figure 2). The lidR package also accounted for overlap between cells when the final output was formed. The batch of LiDAR cells processed together was known as a catalogue of LiDAR data. Using R version 4.2.3, each catalogue was used to define ground points and normalise the height of the point cloud in order to build a canopy height model using the pit-free algorithm to avoid post-processing smoothing steps [50] (Figure 2). Any significant outliers identified from the canopy height model were removed before individual tree detection steps. A variable window size with a local maximal filter was used to analyse the highest point of the point cloud within a given radius to detect treetops [50]. This was used to prevent inaccuracies in treetop detection due to forest density. We used a variable window with predetermined values for trees detected at 5 m tall, which had a window size of 2 m, and trees detected as 20 m tall had a window size of 15 m. Tree height and window size were then scaled using these values. This allowed for smaller trees to be detected, which would typically be obscured by larger trees when using a fixed window size [51].

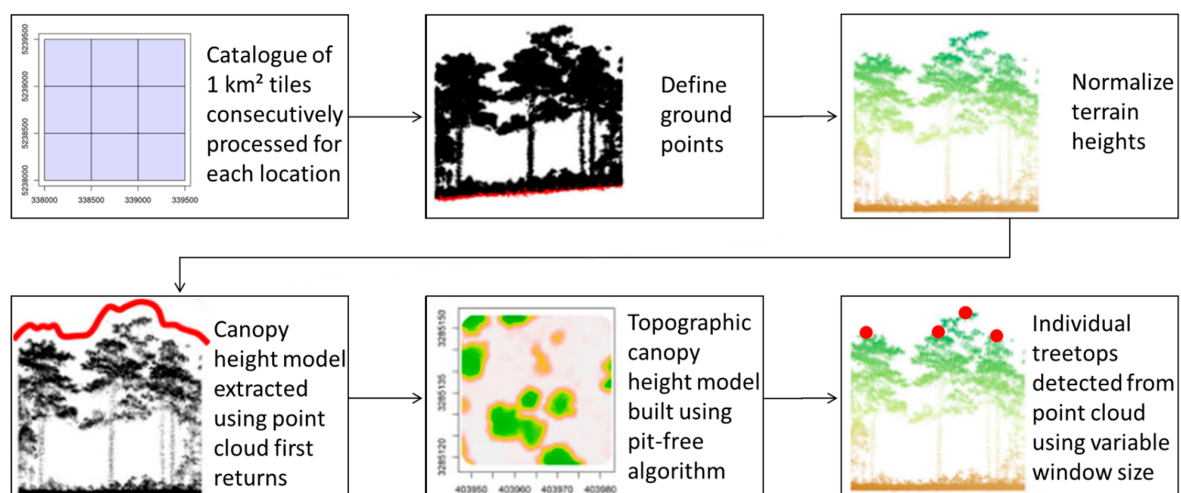


Figure 2. Flowchart summarising the steps taken during data processing of LiDAR point clouds for each study location, run as a catalogue. Steps 2–6 were run consecutively for each tile within a catalogue. Adapted with permission from [25]. Mohan et al., 2021.

We then calculated tree height thresholds for each regional ecosystem type surveyed within the study sites to determine the height of a ‘large tree’ using LiDAR. The threshold

of a large tree for each regional ecosystem was calculated as the average of the top 10% of tree heights minus the standard deviation of the population. These thresholds provided us with similar large tree heights as we observed during field surveys. LiDAR-derived trees were identified and matched to field-surveyed trees through a visual assessment using ArcGIS Pro version 2.9 and the tree coordinates.

2.4. Statistical Analysis

Throughout statistical analyses, tree diameter was analysed using two categories: trees > 30 cm DBH and trees > 50 cm DBH, under the assumptions that tree diameter is significantly affected by and positively scales with tree height when regional ecosystem type is considered (assumption two) and that a larger tree diameter is more likely to possess tree hollows (assumption three). The root mean square error (RMSE) was calculated to give a measure of how accurate LiDAR-derived tree heights were compared to on-ground surveyed tree heights in order to test assumption one. Generalised linear models were constructed for each DBH category to assess the correlation between tree height and tree diameter when considering ecosystem type and the correlation between tree diameter and hollow presence.

After point cloud processing and testing each assumption, the density of LiDAR-detected large trees (above height thresholds for each regional ecosystem) was calculated for each 1 km² grid cell containing a transect (Figure 3). Each transect was then categorised as being in an area with a high or low density of large trees using ArcGIS natural Jenks (Figure 4). The effectiveness of this density mapping was then statistically analysed using two-sample t-tests to test for a difference in means between tree densities of trees > 30 cm DBH and >50 cm DBH from field surveys and high- and low-density LiDAR-derived categories.

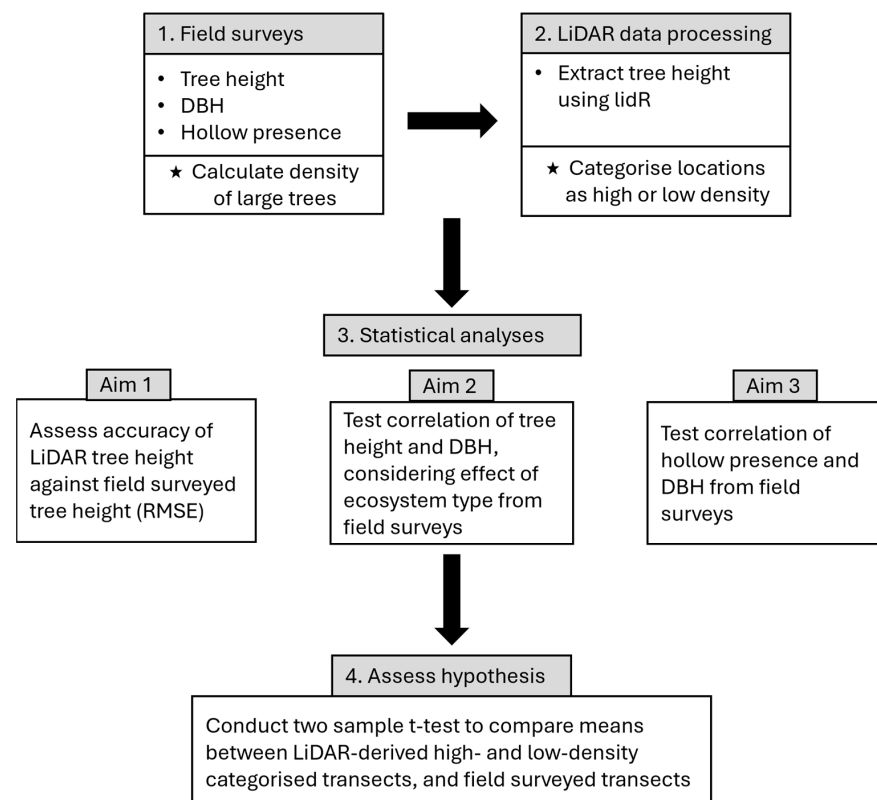


Figure 3. General workflow outline describing steps taken to achieve each major component of this study. Here, RMSE denotes the measure of accuracy; root mean square error. The star ★ points indicate why steps 1 and 2 were conducted.

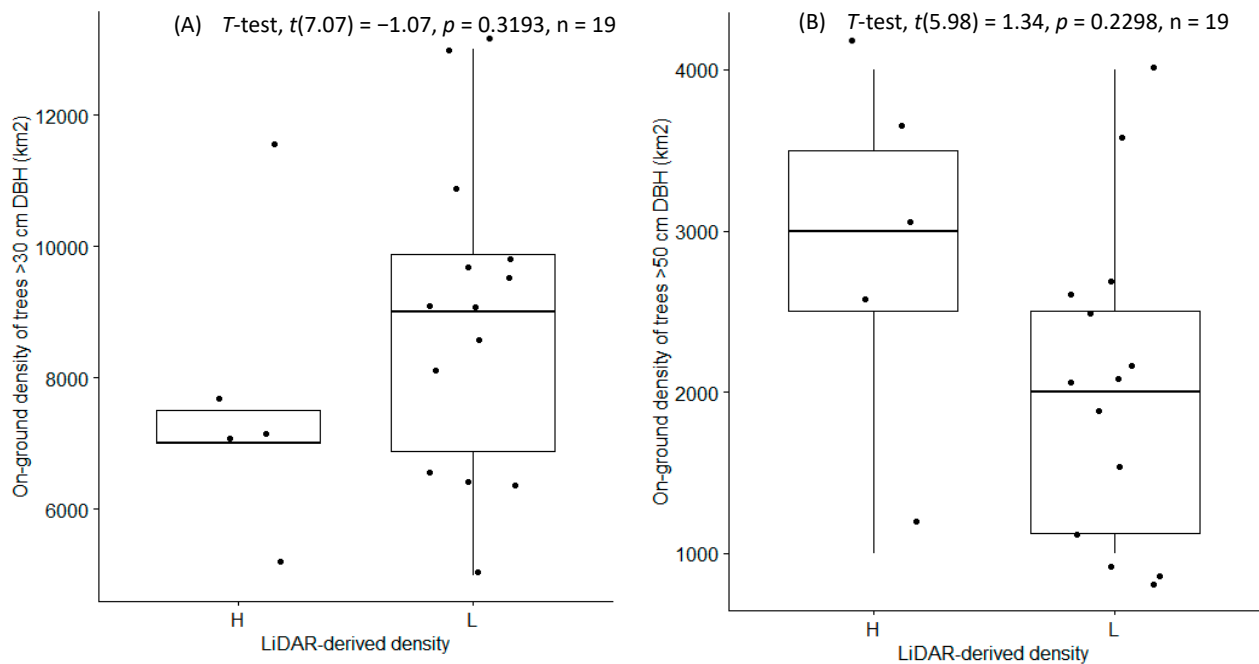


Figure 4. Two boxplots convey the significance of Welch two-sample t -tests, which were used to test the difference in means of on-ground tree densities of trees > 30 cm DBH (A) and trees > 50 cm DBH (B) per km² between two LiDAR-derived tree density categories: high (H) and low (L). The t -test statistics show the degrees of freedom of the relevant T -test and the t -statistic, followed by the p -value and number of observations used in the test.

3. Results

3.1. LiDAR-Derived Tree Height Accuracy

The RMSE between tree heights derived using LiDAR from 2009 and on-ground surveyed trees was 5.75 m for trees > 30 cm DBH, whereas, for trees > 50 cm DBH, the RMSE was 4.69 m. LiDAR tree detection was more accurate for trees > 50 cm DBH than for trees > 30 cm DBH when compared against on-ground measured tree height results. A comparison between on-ground trees surveyed for tree height and trees individually detected using 2009 LiDAR found that 47% of on-ground surveyed trees were able to be identified using 2009 LiDAR. Therefore, 53% of on-ground surveyed trees were unable to be identified using 2009 LiDAR, and the tree height RMSE for these trees could not be computed.

3.2. Correlation Between On-Ground Tree Height and Diameter

Outputs from generalised linear models showed a positive correlation for on-ground surveyed trees between tree diameter and tree height for trees > 30 cm DBH when considering the effect of regional ecosystem type (AIC = 571.52, $R^2 = 0.470$ $p < 0.003$) (Table A1). For trees > 50 cm DBH, there was a weak positive correlation between tree diameter and tree height, even when the regional ecosystem type was included as a factor (AIC = 287.31, $R^2 = 0.57$ $p > 0.05$). Without the effect of the ecosystem type, tree diameter was not strongly correlated with tree height for trees > 30 cm DBH or trees > 50 cm DBH ($R^2 > 30$ cm DBH = 0.014, >50 cm DBH = 0.002).

3.3. Correlation Between On-Ground Tree Diameter and Hollow Presence

For both categories of on-ground trees (>30 cm DBH and >50 cm DBH), there was a positive correlation between tree diameter and hollow presence (Chi-square test: >30 cm DBH $p < 0.0001$, >50 cm DBH $p = 0.002$) (Table A2). Further analysis of generalised linear models us-

ing the height subset data to test the correlation between tree diameter and hollow presence also showed a positive correlation between tree diameter and hollow presence (Chi-square test: >30 cm DBH $p < 0.0001$, > 50 cm DBH $p < 0.0001$). Hollow presence observations of on-ground trees found that presence was higher for trees >50 cm DBH, with 75.3% of trees being hollow-bearing, whereas 54.6% of trees > 30 cm DBH were hollow-bearing. Finally, on average, per transect, 67% of trees found on private properties were hollow-bearing, compared to state-managed forests, where 51% of trees were hollow-bearing.

3.4. Density Mapping

The density of on-ground large trees (>50 cm DBH) was calculated, and as a result, eight transects were classified as high-density and eight transects were classified as low-density. This was compared to the LiDAR-derived density categories, which found that five transects were high-density and eleven transects were low-density. Although LiDAR correctly identified 63.15% of transects when compared against on-ground surveyed transects, outputs from two-sample t -tests showed no statistical significance between the LiDAR-derived average densities of high- and low-density categorised transects (>30 cm DBH p 0.3193, >50 cm DBH p 0.2298) (Figure 4).

4. Discussion

We first tested the following assumptions to thoroughly investigate the hypothesis that areas of high densities of potential hollow-bearing trees can be readily identified by classifying vertical forest structure to refine habitat mapping for hollow-dependent species. After analysis, we were able to confirm that despite being 14 years old, LiDAR from 2009 was able to determine on-ground tree heights with an accuracy (RMSE) of 5.75 m for trees > 30 cm DBH and 4.69 m for trees > 50 cm DBH. We also validated the assumptions that tree diameter could be approximated by tree height when regional ecosystem type is considered for trees > 30 cm DBH and that hollow presence could be approximated by tree diameter. Finally, when LiDAR-derived density categories were compared against on-ground surveyed densities, 63.15% of transects were correctly identified as either high- or low-density transects. However, there was no statistical significance between the LiDAR-derived average densities of high- and low-density categorised transects (Figure 4). The results presented here provide key insights into the necessary considerations and refinements for the use of this method to refine broad-scale habitat mapping for many arboreal species, including the greater glider.

As anticipated, we observed variation in tree heights between different regional ecosystem types likely linked to biotic factors such as soil type and precipitation [52,53], and as a result, tree height thresholds were calculated for each ecosystem type to address variations in tree height caused by forest types [39]. However, we also observed height variations within the same regional ecosystem types. Therefore, prior to the establishment of height thresholds for each regional ecosystem type using LiDAR, future studies should incorporate the effects of site history, including logging and fire history. This may improve the accuracy of tree height mapping, as increased occurrences of logging and high intensity or frequent wildfire have a higher likelihood of removing tall, canopy species, in comparison to sites with limited disturbance [54]. It is noteworthy that during field surveys, we observed evidence of recent fires in many transects and overall higher levels of disturbance in state forests compared to private properties. Some transects had an abundance of invasive weeds, evidence of grazing (cattle present) and significant loads of very dry debris, which may fuel extremely intense and hot wildfires (Figure A1). The use of up-to-date LiDAR would include these changes in logging, grazing and fire history, which the 2009 LiDAR did not capture [10].

However, a key component of this study was to investigate if freely available 14-year-old LiDAR had the capacity to measure tree heights to infer tree diameter and hollow presence. Despite results showing that LiDAR from 2009 can be used to detect tree height when compared against field surveys from 2023, clearly, the use of up-to-date LiDAR would be advantageous, particularly when surveying recently disturbed landscapes [1]. The authors of [55] investigated the effects of selective timber logging compared to fire regime on parts of Bauple State Forest on the Fraser Coast. This study identified that fire regimes can be more detrimental to the landscape than logging impacts, particularly regarding high-intensity burns, which we have seen more frequently across Australia in recent years. These disturbances may not be captured on comparatively outdated LiDAR; therefore, this may impact the results of hollow presence and tree height analyses [56].

The significant gap between 2009 LiDAR and field surveys conducted in 2023, in combination with the use of unsupervised learning techniques for treetop detection, may explain the relatively low accuracy of tree height measurements when compared to on-ground field surveys (RMSE 5.75 m). A study by [10] using the *lidR* package and unsupervised learning local maxima algorithms to determine treetops from the point cloud found a much higher accuracy (RMSE 0.14 m). However, this study used LiDAR collected using a UAV, which allowed for highly dense and fine-scale accurate point cloud collection.

The use of unsupervised learning techniques, such as the local maxima algorithm used in the *lidR* package, is known to cause errors when distinguishing between individual treetops for complex forest stands [10]. Our study observed that over 50% of tree heights measured during field surveys were unable to be identified using LiDAR and were therefore excluded from tree height accuracy analyses. However, missing LiDAR-derived tree height points may also be explained by possible GPS inaccuracies during field surveys, with trees being below the height thresholds and the age gap between LiDAR data collection and field surveys.

Alternatively, the use of deep learning for remote sensing can significantly improve accuracy for individual tree detection and tree crown delineation, with some methods seeing 92% accuracy for individual tree detection from imagery using UAVs [57]. However, deep learning methods, in combination with UAV LiDAR data and the acquisition of up-to-date data, can be significantly more time-consuming, costly and require particular expertise to utilise [26,27,58]. The methodology presented in this study conveys that the use of accessible methods is robust enough to identify areas of potential habitat trees and measure tree height using an unsupervised machine learning approach and freely available LiDAR across a large spatial extent.

Analysis of field survey data showed a positive correlation between tree diameter and tree height when considering the effect of regional ecosystem type for trees > 30 cm DBH. This highlights the importance of ensuring that ecosystem types are incorporated into geospatial modelling of tree size to inform the mapping of hollow-bearing trees [59]. For both DBH categories, the transect was a similarly significant factor in predicting tree height. While the effect of regional ecosystem type may explain differences in forest type, the transect may account for finer scale individual site factors such as the effects of fire, logging, grazing history, rainfall, slope or other individual site environmental factors [60,61]. Unfortunately, there was a limited number of trees > 50 cm DBH within our field transects; therefore, we were unable to find a strong correlation between tree height and diameter, considering the ecosystem type, for trees above this size. This emphasises both the scarcity of large, potentially hollow-bearing trees and that the relationship between tree height and tree diameter for trees > 50 cm and > 100 cm DBH still requires investigation. This is especially important because these larger trees would be more beneficial to greater gliders

as potential hollow-bearing trees, as they are more likely to have hollow diameters over 10 cm [62].

Hollow presence was positively correlated with tree diameter for both DBH categories (>30 cm DBH 54.6% presence, >50 cm DBH 75.3% presence). The findings by [62] support that trees > 50 cm DBH are more likely to possess hollows than trees < 50 cm DBH. Furthermore, this study also explores the significance of tree age to predict hollow presence, where trees aged between 74 and 100 years old are likely to exhibit small hollows, and trees over 140 years old with a DBH > 124 cm are most likely to exhibit hollows more suitable in size for greater gliders [8,39]. Unfortunately, due to the value of trees > 100 cm DBH to the logging industry, trees of this size are increasingly rare; thus, for this study, we could not investigate the relationship of hollow presence for trees > 100 cm DBH, despite their significant importance to greater gliders. However, it is also important to note that trees > 30 cm DBH are often used by greater gliders as feed trees and can also be potential future habitat trees; therefore, their significance should not be overlooked during future planning and forest management [8]. Furthermore, during field surveys, a greater proportion of substantially large tree hollows were observed on privately owned sites in comparison to state-managed forest sites. This may be due to the differences in forest management, with privately owned sites experiencing significantly less disturbance in comparison to current and ongoing logging practices, and the observed high-intensity fires within state forests [63]. This would further support the prioritisation of conservation efforts to manage habitat trees as a key resource for greater gliders by identifying potentially threatened areas.

Finally, although the categorization and mapping of large tree densities did not significantly correlate to on-ground densities of trees for either DBH category, the use of existing 2009 aerial LiDAR, paired with unsupervised machine learning techniques, was still able to correctly identify 63.5% of all surveyed transects as high- or low-density sites. The lack of statistical significance is likely either due to the limited sample size or the scale at which density was calculated. Our results suggest that large tree density could be classified at a finer scale to provide more accurate mapping and tree identification to inform conservation outcomes. We expect that a smaller scale, such as 1 ha (0.01 km²) as developed by [64], would provide more accurate density mapping in comparison to the 1 km² cell sizes used in this study to effectively map densities of large potential habitat trees at both local and landscape scales. Therefore, with further refinements, the broad classification of high- and low- habitat tree density sites can be a step to help identify areas of interest (with more habitat trees) at landscape scales and enable us to refine the current broad mapping of greater glider habitats in the Fraser Coast region.

Future work should investigate the presence of greater gliders at the surveyed high-density sites identified from refined greater glider habitat mapping across the Fraser Coast. The results presented in this study indicate that future research and refinement of the methodology is needed in order to accurately map and identify areas with a high density of potential hollow-bearing trees. To increase the accuracy of this approach, it is recommended that future research should refine the scale at which LiDAR was processed from 1 km² to 1 ha. Studies should also analyse specific tree species' height and diameter allometry and the fire history data when defining thresholds for large trees in a regional ecosystem type. This would increase the accuracy of individual tree detection. Up-to-date, high-quality LiDAR and deep learning geospatial approaches to individual tree detection would significantly increase the accuracy of identifying potentially hollow-bearing trees. However, this study aims to develop an accessible and transferrable geospatial approach to refine habitat mapping, and, here, we have shown that cost-effective, freely available LiDAR and simple geospatial analysis techniques can be used to identify these areas of potentially hollow-bearing trees.

5. Conclusions

This study aimed to investigate whether a simple geospatial analysis approach based on freely available data can be used to analyse vertical forest structure to refine habitat mapping by identifying potentially hollow-bearing trees. We found that LiDAR, despite being collected 14 years prior to field surveys, could be used to identify treetops. Our second assumption that tree height correlates to tree diameter when considering ecosystem type was validated, as was our third assumption that tree diameter correlates to hollow presence. To assess the hypothesis that a simple geospatial analysis approach could identify areas of high densities of potential hollow-bearing, we used LiDAR from 2009 to identify tall trees, which are more likely to have a large diameter, correlating to hollow presence. Here, we have shown that this accessible, simple and transferable approach was able to identify areas with high densities of potentially hollow-bearing trees. Our study has created a basis for future work, and we have presented further refinements of these methods to more accurately identify areas with high and low densities of potential hollow-bearing trees. Although more complex approaches, such as the combination of new high-resolution LiDAR and deep machine learning, would increase accuracy, we have shown here that the application of geospatial analysis for the refinement of habitat mapping can be achieved using free and accessible methods. It is important to make geospatial analysis techniques more approachable for land managers by ensuring that they are cost-effective and easy to implement.

The methodology developed in this study could be used to aid management bodies to more easily conserve hollow-bearing trees by identifying high densities of large trees to be protected or areas with low densities of large trees that could be further enriched. These areas may include stands of potential recruitment trees or regrowth forest, which could implement artificial hollow carving or nest box deployment initiatives to enhance the current habitat for hollow-dependent species. Finally, the presence of greater gliders should be investigated at locations identified as having a high density of potential hollow-bearing trees. This would be the final step to confirm the effectiveness of the method developed in this study to refine habitat mapping for hollow-dependent species using geospatial analysis.

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Data Availability Statement: Individual tree detection code used the lidR package in R version 4.2.3 and was based on the guidelines set out by Roussel et al. (2020) and Roussel and Auty (2023) [19,20]. The LiDAR data “Fraser Coast 2009 Project” used for this study can be accessed through Queensland Spatial Catalogue—QSpatial, which is retrieved from <https://qldspatial.information.qld.gov.au/catalogue/custom/detail.page?fid=%7BE8CEF5BA-A1B7-4DE5-A703-8161FD9BD3CF> (accessed on 31 July 2022).

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Abbreviations

The following abbreviations are used in this manuscript:

DBH Diameter at breast height

RMSE Root mean square error

Appendix A



Figure A1. (a–c) Excessive fuel loads and invasive species within state forests. (d) This is compared against the openness on private property. All photos were taken within similar regional ecosystems during field surveys.

Table A1. Generalised linear model performance output statistics analysing the relationship between on-ground tree height and various model predictors for both DBH categories (>30 cm DBH and >50 cm DBH). RE denotes regional ecosystem. Regional ecosystem and transect were both factor variables for each model.

Model Predictors	R^2		AIC	
	>30	>50	>30	>50
DBH category (cm)				
None	0	0	619.34	315.37
DBH	0.01	0.01	620.03	317.31
DBH + RE	0.47	0.57	571.52	287.31
DBH + Transect	0.59	0.73	570.79	290.19

Table A2. Binomial generalised linear model performance output statistics analysing the relationship between hollow presence and various model predictors for both DBH categories (>30 cm DBH and >50 cm DBH), using the DBH dataset. RE denotes regional ecosystem. Regional ecosystem and transect were both factor variables.

Model Predictors	R^2		AIC	
	>30	>50	>30	>50
DBH category (cm)				
None	0	0	451.17	97.04
DBH	0.09	0.09	412.21	89.98
DBH + RE	0.11	0.13	410.30	94.45
DBH + Transect	0.16	0.43	415.32	94.31
DBH + RE + Transect	0.16	0.43	418.63	97.85

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