GREENER, COOLER AND MORE SUSTAINABLE COMMUNITIES: MANAGING THE URBAN FOREST INTO THE FUTURE USING GEOSPATIAL DATA.

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Abstract

Whether the value of the urban forest is defined by its socioeconomic benefits or its monetary value, paramount to the understanding of the importance of trees within urban environments is a quantitative understanding of how many trees there are and their spatial distribution throughout the community. City-wide assessments of urban tree canopy cover, e.g., McPherson et al., (2011), Jacobs et al. (2014) and S.J. Holt (2020), have become common foundations for national and local governments to measure, assess and increase the number of trees and green spaces within their government areas (Ordóñez et al., 2019). Accurate benchmarks and ongoing assessments of tree canopy cover and green spaces allow local government agencies to continuously review the performance of ongoing greening initiatives as well as ensuring that future policies are not only adequate, but achievable (Amati et al., 2017; Hurley, 2020)

Light Detection and Ranging (LIDAR) (**Fig. 1**) has become an industry standard remote sensing tool to map vegetation ecosystems (Coops et al., 2021) and quantify plant attributes and urban environments (Wang et al., 2019; Wang et al., 2020; Holt, 2020). Over the past year, Aerometrex has worked alongside urban environmental experts at the state and local government level to develop city-wide, LIDAR-derived tree canopy assessments, designed to provide a holistic understanding of the urban forest across large areas of interest and at a range of resolutions (council, suburb, property, or unit area) on both public and private land. Aerometrex urban forest data suite gives environmental experts and policy makers at all levels of government a critical understanding of the state of the urban forest at a given snapshot in time, while also providing them with the spatial and temporal context needed to value their green assets effectively and accurately.

Presented here are the results of three case-studies undertaken by Aerometrex utilising LIDAR to measure the characteristics and spatial distribution of the urban forest across large areas of interest:

i. Tree Canopy Coverage Benchmark, Metropolitan Adelaide, 2018/19 – Undertaken on behalf of The Department of Environment and Water (DEW) and metropolitan local government climate change adaptation groups with the aim of producing a city-wide benchmark for tree canopy coverage across Metropolitan Adelaide.

ii. City-wide plantable space assessment, Metropolitan Adelaide, 2018/19 – Commissioned by Green Adelaide and DEW to identify priority areas in greatest need of greening investment and inform future project design to provide the greatest benefit to the community.

iii. High resolution tree canopy change detection and classification, City of Unley, 2018-2021 – Carried out in collaboration with City of Unley to develop methodologies to quantitatively measure and accurately classify the changes in tree canopy between two epochs.

In combination, these case studies showcase the ability of LIDAR to quantify the urban forest and green infrastructure at the city scale, and measure how it is changing with time – all derived from a single data capture to provide the most robust yet cost-effective foundation possible for the valuation of green assets and measure their benefit to the community.

1. Introduction

Increasing urban greenness, vegetation and urban tree canopy cover has become one of the most critical considerations for strategic planning within state and local government organisations (Amati et al., 2017). Urban trees and community green spaces have been identified as an important tool that can be used by policy-makers to mitigate the many negative environmental effects of urbanisation (Roy et al., 2012).

Numerous studies have shown that the presence of urban trees can provide socioeconomic value to the community through numerous positive effects on the urban environment, such as economic benefits (Payton et al., 2008; Elmqvist et al., 2015; Donovan et al., 2019), positive effects on community health, well-being and safety (Kuo and Sullivan, 2001; McPherson et al., 2011; Kardan et al., 2015), improved air quality and storm water attenuation (Berland, 2012; Nowak et al., 2014; Selmi et al., 2016; Grey et al., 2018), combatting climate change through carbon sequestration (Brilli et al., 2019) and increasing community resilience to the effects of climate change by reducing the effects of urban heat islands (Tan et al., 2016; Rashid et al., 2020; Cheela et al., 2021). Translating the socioeconomic benefits of the urban forest into economic terms, which are often central to decision making processes and policy development, can be challenging (Rogers et al., 2017; Wang et al., 2018). Despite this, it can be advantageous to quantify the monetary value of trees as it enables a quantitative understanding of the balance of costs and benefits associated with green assets, leading to the effective integration of economic assessments into decision making processes at state and local governments (Jones and Davies, 2017; Song et al., 2018).

Whether the value of the urban forest is defined by its socioeconomic benefits or its monetary value, paramount to the understanding of the importance of trees within urban environments is a quantitative understanding of how many trees there are and their spatial distribution throughout the community. City-wide assessments of urban tree canopy cover, e.g., McPherson et al., (2011), Jacobs et al. (2014) and S.J. Holt (2020), have become common foundations for national and local governments to measure, assess and increase the number of trees and green spaces within their government areas (Ordóñez et al., 2019). Accurate benchmarks and ongoing assessments of tree canopy cover and green spaces allow local government agencies to continuously review the performance of ongoing greening initiatives as well as ensuring that future policies are not only adequate, but achievable (Amati et al., 2017; Hurley, 2020). For a city-wide assessment of the urban forest to yield actionable results, it is critical that it accurately accounts for trees on private as well as public land, as private land can account for over 50% of both urban tree cover and open space, thus, making a large contribution to the urban forest and it's positive benefits (McPherson, 1998; Fuller and Gaston, 2009; Schmitt-Harsh et al., 2013; Klobucar et al., 2020).

Light Detection and Ranging (LIDAR) (**Fig. 1**) has become an industry standard remote sensing tool to map vegetation ecosystems (Coops et al., 2021) and quantify plant attributes in both native vegetation (Van Leeuwen and Nieuwenhuis, 2010; Li et al., 2015; Hagar et al., 2020), managed forests (Silva et al., 2016; Dalla Corte et al., 2020; Leite et al., 2020) and urban environments (Wang et al., 2019; Wang et al., 2020; Holt, 2020). LIDAR is often preferred to other passive and active remote sensing technologies (e.g. Synthetic Aperture Radar, SAR) for the purposes of measuring vegetation as LIDAR provides greater sensitivity to changes in vegetation structure (Dong and Chen, 2018b). LIDAR-derived metrics can also provide a more accurate description of the canopy coverage and be more sensitive to small-scale changes than random point classification methods such as iTree (Parmehr et al., 2016). Furthermore, LIDAR can provide greater positional accuracy and three dimensional detail compared to AI-derived canopy maps (e.g. Abdollahi and Pradhan, (2021)) as LIDAR measures the vegetation explicitly in three dimensions, free of perspective effects (Dong and Chen, 2018a).

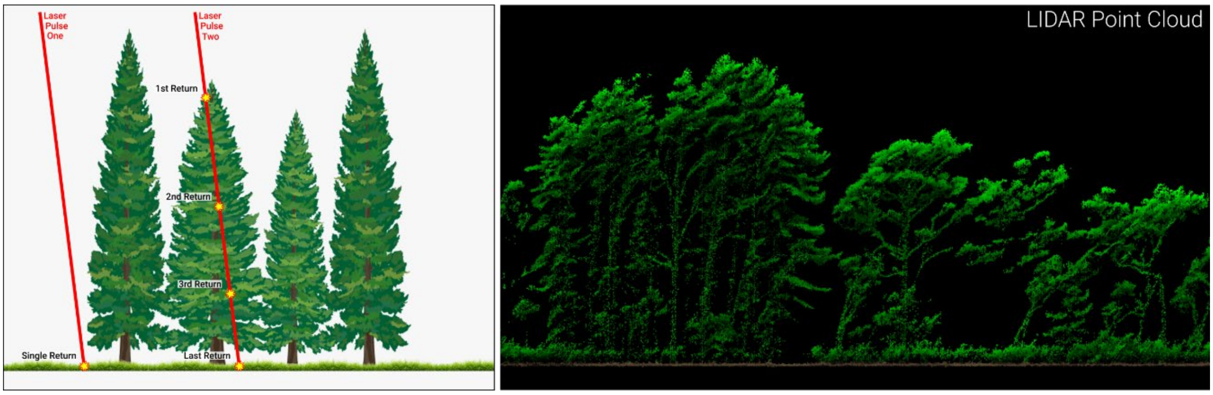

Figure 1 *- LIDAR explicitly images the landscape in three dimensions by measuring the time taken for a laser pulse to travel from the sensor in the aircraft, to the ground surface, and for the pulse to be reflected back to the sensor. LIDAR pulses have the ability to penetrate tree canopy and map the internal structure of the tree (left) to produce an accurate three-dimensional point cloud model of the vegetation (right).*

Over the past year, Aerometrex has worked alongside urban environmental experts at the state and local government level to develop city-wide, LIDAR-derived tree canopy assessments, designed to provide a holistic understanding of the urban forest across large areas of interest and at a range of resolutions (council, suburb, property, or unit area) on both public and private land. Aerometrex urban forest data suite gives environmental experts and policy makers at all levels of government a critical understanding of the state of the urban forest at a given snapshot in time, while also providing them with the spatial and temporal context needed to value their green assets effectively and accurately.

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In combination, these case studies showcase the ability of LIDAR to quantify the urban forest and green infrastructure at the city scale, and measure how it is changing with time – all derived from a single data capture to provide the most robust yet cost-effective foundation possible for the valuation of green assets and measure their benefit to the community.

2. Project Datasets

All three case studies presented here utilize LIDAR data captured using a RIEGL VQ-780i sensor, with a vertical accuracy of 10cm and classified to Aerometrex's Type 2 standard (**Fig. 2**), which includes manual refinement of the ground, building and high vegetation classes (ASPRS, 2019). The 2018 LIDAR survey used in all three case studies was captured in April 2018 and was expanded to include full coverages of sixteen metropolitan councils in November 2019. In total, the dataset covers 1,706 km^2 of metropolitan Adelaide (**Fig. 3**). The third case study incorporates a subsequent LIDAR capture in April 2021 across City of Unley (14.5km^2) and is compared to the 2018 data across the same area to quantify change detection. Both datasets have a minimum point density of – 8-12 pts.m^{-2}. For all projects, following consultation with council representatives, a tree was defined as any vegetation above three metres in height, as it is above this height that the tree begins to provide shading.

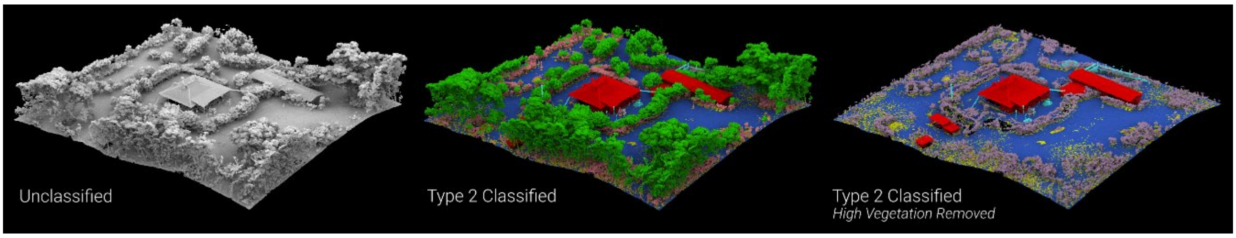


***Figure 2** – Left: unclassified point cloud visualised using ambient occlusion (REF). Middle: Type 2 classified point cloud with ground (blue), low and medium vegetation (yellow and pink), high vegetation (green), building (red) and unclassified (aqua). Right: the same classified point cloud with the high vegetation class removed.*

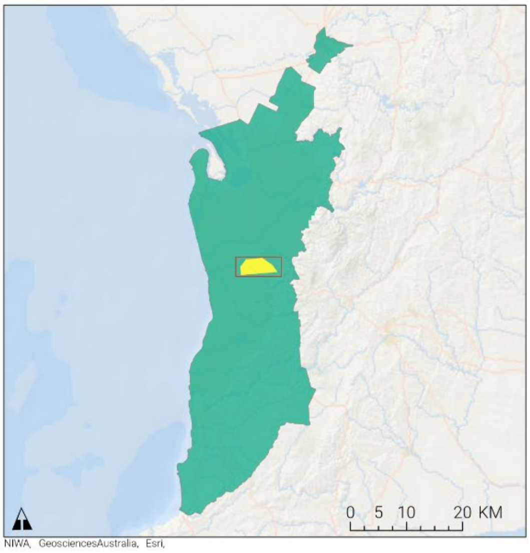


***Figure 3** – Left: Map showing the full coverage of the 2018/19 LIDAR capture (green) as well as the area covered by the City of Unley 2021 capture.*
Top: a zoomed in view of the urban area covered by the 2021 LIDAR survey.

3. Case Study 1 – Tree Canopy Coverage Benchmark, Metropolitan Adelaide, 2018/19

3.1 Project Summary

In 2019 Aerometrex was commissioned by DEW and four metropolitan local government climate change adaptation groups (representing sixteen individual councils) to produce a quantitative tree canopy coverage benchmark across metropolitan Adelaide. The core aim of this project was to provide all participating LGAs and the State government with a quantitative, spatially explicit benchmark for tree canopy coverage in 2018/19. This benchmark would then form the foundation for the assessment of the effectiveness of greening initiatives across the city in coming years. As part of this project Aerometrex developed a suite of LIDAR-derived urban forest datasets (**Fig. 4**) to provide each participating council with not only a tree canopy coverage benchmark, but also an understanding of the vertical distribution of tree canopy (Canopy Height Model & Stratification Maps), the distribution of tree canopy across land ownership and land use types as well as a measure of the spatial distribution of tree canopy coverage across the city, independent of biases associated with measuring at the per council or per suburb level (Tree Canopy by Unit Area). The full set of results and associated graphical reports can be viewed at DEW's Urban Heat and Tree Mapping viewer (Enviro Data SA, 2021).

3.2 Methodology

The geoprocessing methodology used to extract all tree canopy metrics from the LIDAR point cloud were based on those presented in Dong and Chen, (2018b) and Holt (2019). Land Use and Land Ownership statistics were generated using parcel definitions provided by Department of Planning, Transport and Infrastructure.

3.3 Results

Tree Canopy Height

The city-wide Canopy Height Model (CHM) for trees above three metres in height revealed that the average tree canopy height across metropolitan Adelaide is 10.1 m with a standard deviation of 5.5 m (minimum height of three metres). The highest non-native tree canopy can be found in Bone Gully Forest, Kangarilla and the tallest native vegetation can be found in the Boulevard of Gums, Belair National Park, Mitcham (**Fig. 5**), which are 48.3m and 48.2m above ground respectively. Canopy Stratification Maps for all sixteen participating LGAs show that tree canopy between three and ten metres in height constitutes the majority of tree canopy cover across the city (**Fig. 5**).

Tree Canopy Coverage

The overall tree canopy cover for the metropolitan Adelaide area (as defined by (Holt, 2020)) for 2018/19 was 23.37% (**Fig. 6**). The tree canopy coverage for local government areas wholly within the LIDAR capture area ranges from 48.81% in City of Mitcham to 9.89% in the City of Port Adelaide Enfield. The average tree canopy cover across all participating LGAs was 23.16%. The tree canopy cover for suburbs wholly within the LIDAR capture area ranges from 71.8% in Waterfall Gully to 1.7% at Parafield. When measured by unit area, the average tree canopy coverage across metropolitan Adelaide is 22.7% within a standard deviation of 23.0%. For twelve out of the fourteen LGAs within the survey area, the majority of tree canopy covers residential land use areas and private land ownership areas. In some cases, as much as 50% of the tree canopy exists on residential or private, e.g. City of Unley, Town of Walkerville and City of Onkaparinga.

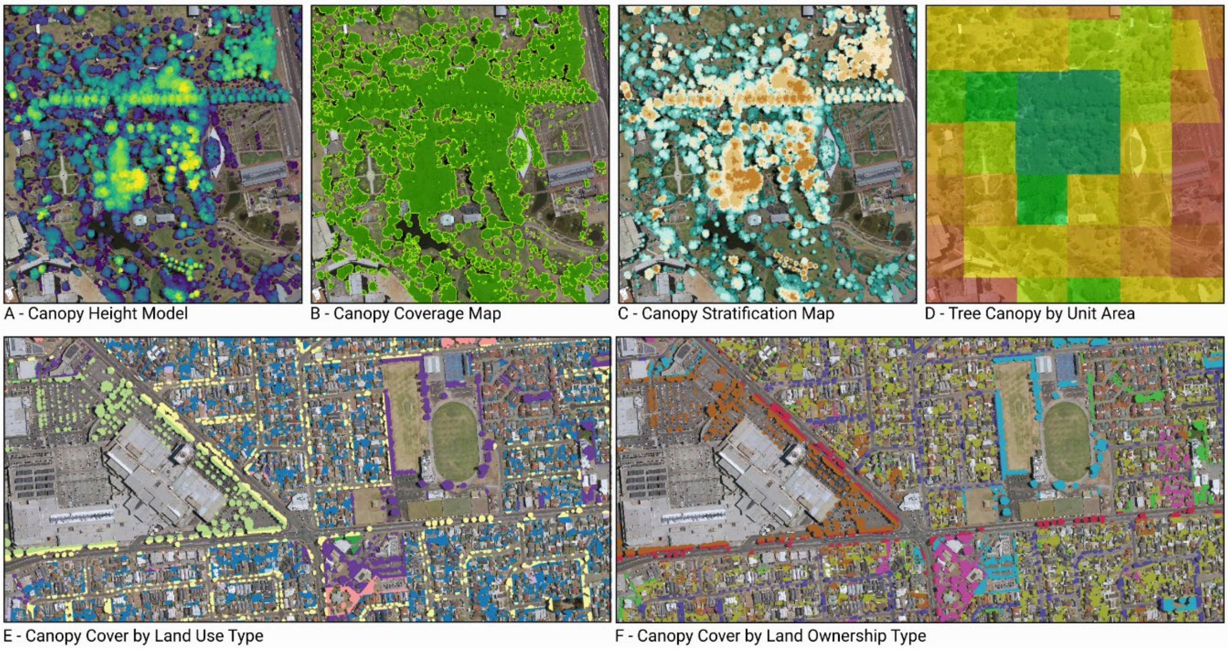


Figure 4 *– Top: The four key products that comprise Aerometrex's urban forest data suite. A: Canopy Height Model (CHM), a discontinuous raster showing the height of tree canopy above ground. B: Tree Canopy Coverage, showing the precise area covered by tree canopy. C: Canopy Stratification, showing the coverage of tree canopy within defined height strata. C: Canopy Cover by Unit Area, showing the percentage tree canopy coverage per 100 m by 100 m unit area cell. Bottom: Tree Canopy Cover by Land Use and Ownership generated by intersecting Tree Canopy Cover will parcel boundaries.*

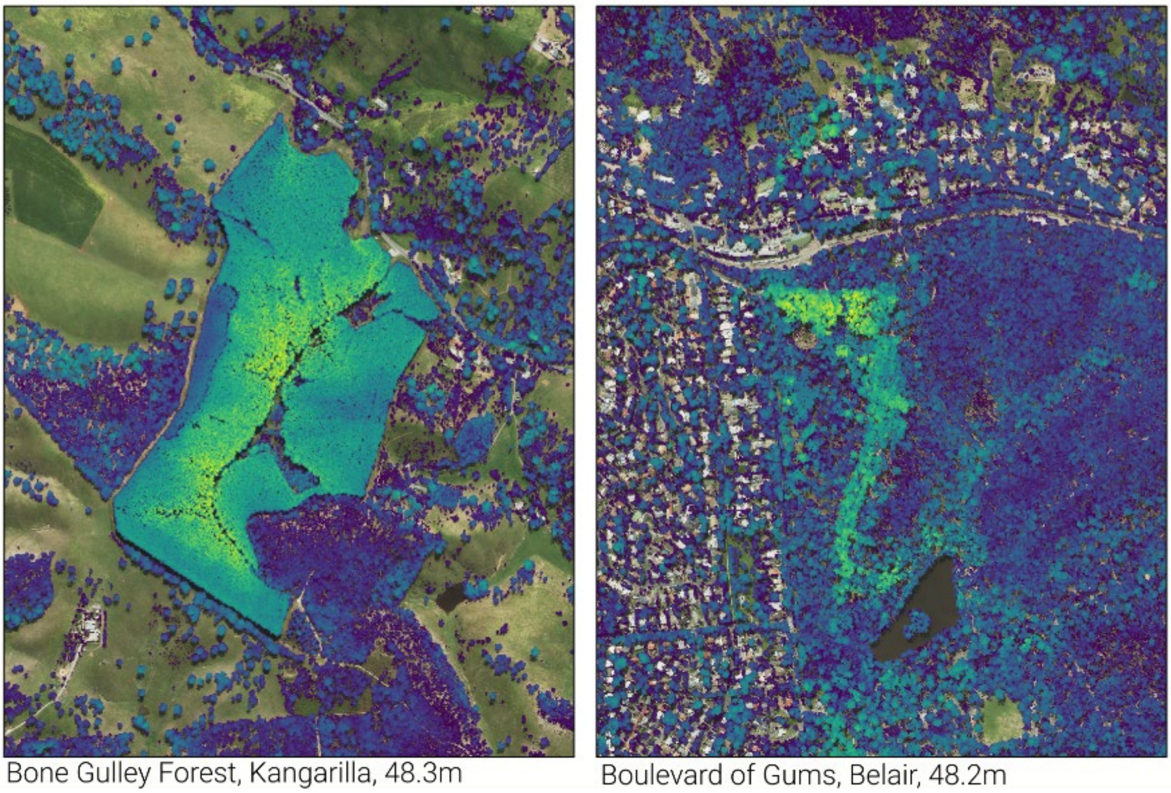
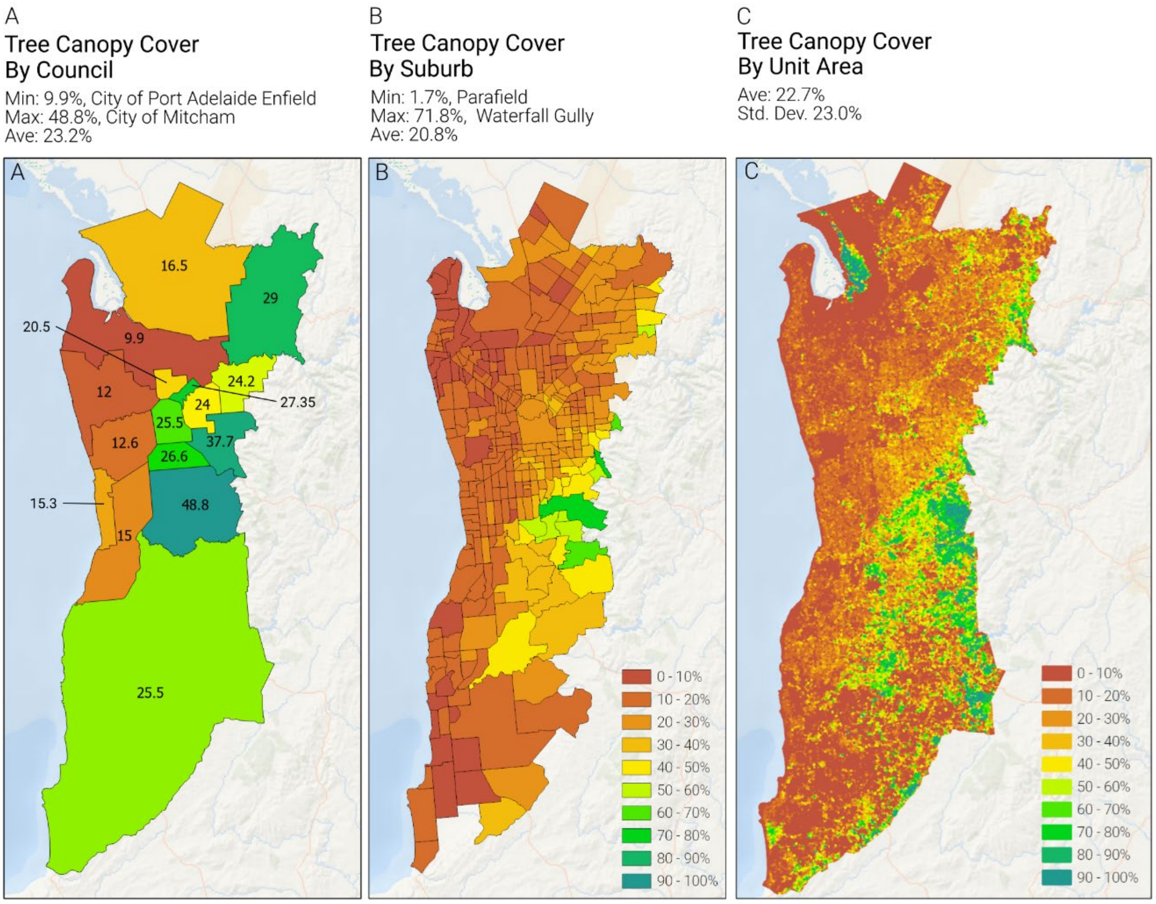


Figure 5 *– CHM of the tallest non-native and native tree canopy in metropolitan Adelaide.*
Left: non-native vegetation in Bone Gully Forest. Right: native vegetation in Belair National Park.

3.4 Key Project Outcomes

This project provided accurate, spatially explicit LIDAR-derived tree canopy coverage benchmarks for metropolitan Adelaide (23.37%) as well as individual benchmarks for all sixteen participating LGAs. The datasets provide both the State and local governments in South Australia with a nationally leading, spatially explicit benchmark that can be used to track the change in tree canopy coverage in years to come and assess the effectiveness of ongoing greening initiatives. When assessing the tree canopy cover by LGA extent or suburb extent, the true distribution of tree canopy can be hidden due to areas associated with coarse sampling domains (Dark and Bram, 2007). Added to this, the tree canopy cover of any given LGA extent is biased by the land uses within it. For example, the tree canopy coverage in the City of Mitcham is positively biased by abundant national parks and reserves and the City of Onkaparinga's is negatively biased by arable agriculture. Canopy Cover by Unit Area provides an unbiased representation of the tree canopy cover and a robust description of the spatial distribution of tree canopy cover across the city, also allowing for a better understanding of the representative tree canopy coverage of denser urban areas, in this case 0-20%. The tree canopy by land use and land ownership results provide quantitative evidence of one of the key challenges facing LGAs: that despite being tasked with increasing tree canopy cover to meet greening targets, in many cases they do not control enough of the tree canopy to meet those targets. This highlights the critical role that private landowners play in increasing the tree canopy cover across the city and the importance of initiatives that target public awareness of urban greening initiatives (Ordóñez-Barona et al., 2021).



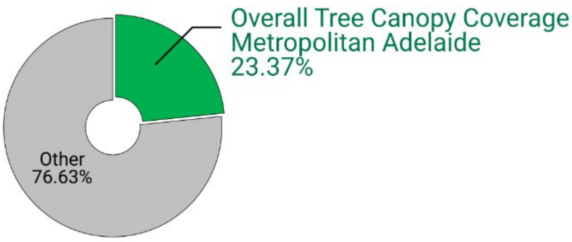


Figure 6 *– Distribution of tree canopy coverage across Metropolitan Adelaide, measured per LGA area (A), Suburb wholly within the LIDAR survey (B) and per 100 m by 100 m unit area. The overall tree canopy coverage for metropolitan Adelaide for 2018/19 was 23.37%. Base-maps: NWA, Geoscience Australia, Esri.*

4. Case Study 2 – City-wide plantable space assessment, Metropolitan Adelaide, 2018/19

4.1 Project Summary

The primary objective of the project was to produce a 50cm resolution, fully semantic classification of permeable and impermeable surfaces across 1,305 km^2 of metropolitan Adelaide (Holt, 2021). Green Adelaide and DEW funded the project to allow experts to use the permeable and impermeable surface data to form a detailed understanding of the amount and spatial distribution of plantable space (permeable ground surfaces), assess the progress and feasibility of current greening initiatives, and develop better informed targets and policies for the coming years. When combined with the 2018/19 tree canopy benchmark, these datasets can be used to not only identify areas in greatest need of greening investment, but also identify areas with the greatest greening potential and inform the development of long term greening policies (Wu et al., 2008; Bravo-Bello et al., 2020). Extending the classification into a full semantic classification of the urban environment meant that the final output could also be applied to detail surface water run-off and flood modelling during high rainfall events (Sugg et al., 2014; Sarkar Chaudhuri et al., 2017; Hung et al., 2018).

The final project output, consisted of a 50cm resolution semantic classification of the urban environment, comprised of five classification classes (developed in collaboration with government end-users):

1. *Impermeable* – impermeable ground surfaces such as pavement, concrete and roads.
2. *Permeable/Plantable Space* – permeable ground surfaces including bare soil and grass.
3. *Impermeable Above-ground Object* – Above ground features that are deemed to be impermeable in nature including buildings, tree canopy overhanging roads and other infrastructure between 0.25-3m in height with a relative NDVI below 0.15.
4. *Permeable Above Ground Object* – Above ground features that are deemed to likely be permeable in nature including trees and vegetation between 0.25-3m in height with a relative NDVI above 0.15.
5. *Water body* – Including the ocean, lakes, rivers, dams and large pools.

4.2 Methodology

Figure 7 outlines the methodology used to produce the permeable vs impermeable surface classification. The project utilised two key datasets, a set of LIDAR-derived raster inputs including a normalized digital surface model (nDSM) and intensity map, as well as four band multispectral imagery (R:G:B:NIR) captured near simultaneously to the 2018/19 LIDAR dataset. These datasets were combined with secondary, vector feature datasets used to refine the classification, including LIDAR-derived building footprints, tree canopy cover and waterbodies and AI-derived road extents. The semantic classification was carried out in two stages. Stage One (**Fig. 7**) consisted of classifying ground surfaces as either permeable or impermeable using an end-to-end trained Feature Pyramid Network (FPN) (Lin et al., 2017). Stage Two utilized the secondary vector feature datasets in a rule-based, Object Based Image Analysis workflow (Blaschke, 2010) to produce a refined sematic classification (**Fig. 7**).

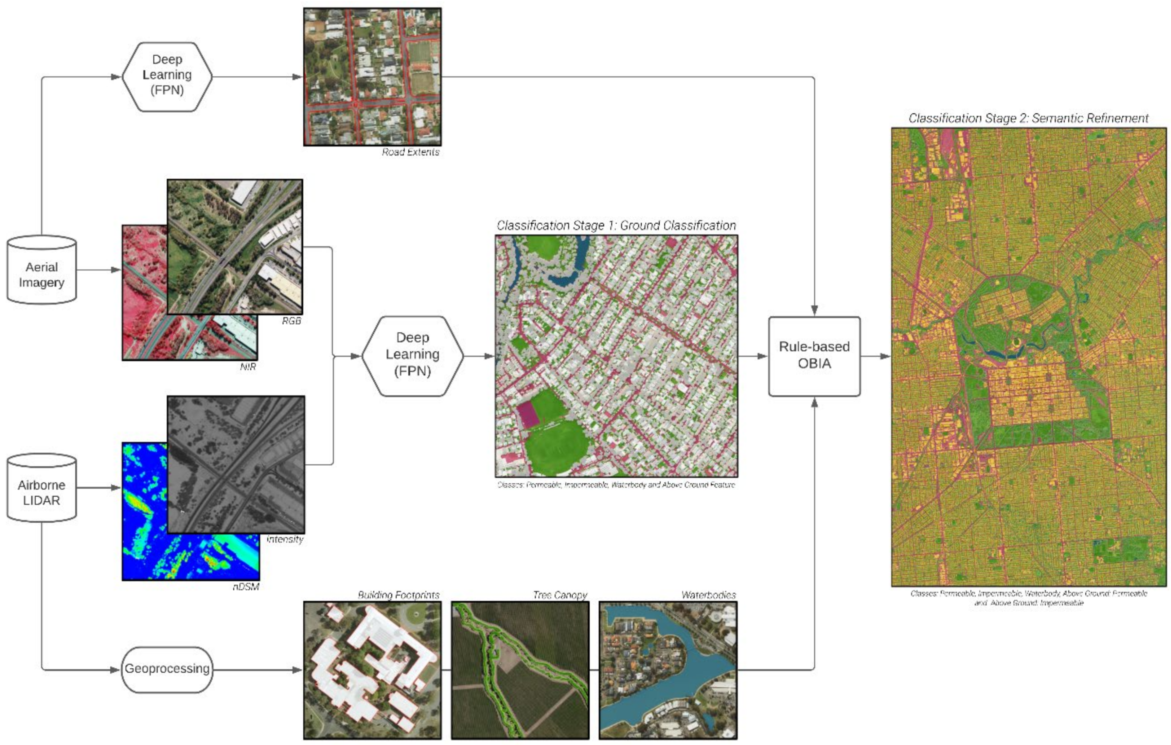


Figure 7 *– Graphical workflow showing methodology used for the two-stage semantic classification of Permeable surfaces (Plantable Space) and Impermeable surfaces, across the study area.*

4.3 Results

Classification Accuracy

The performance and accuracy of the FPN classifier was assessed using a manually labeled validation dataset which consisted of 10 separate tiles, each with an area of 1 km^2. Ground and above ground objects within each validation tile were manually classified using an Object Based Image Analysis workflow, utilising our high-resolution imagery as a reference (spatial resolution of 7.5cm). In total, over 27 million pixels were manually labeled, corresponding to an approximate area of 7km^2. A direct comparison between the classification of each pixel in the validation dataset and classified dataset was used to assess the performance of the FPN classifier. It is important to note that the data used for validation was not part of the data used to train the FPN classifier. The FPN-derived ground classification has an overall accuracy of 89.45% and an overall Kappa Index of Agreement of 0.78 (Excellent; Richards, (1999)).

Permeable vs Impermeable Surface Distribution

Figure 8 shows an example of the output classification, as well as the distribution of permeable and impermeable surfaces within the 2018 LIDAR survey extent, which covers the majority of Adelaide's urban areas and corresponds most closely with the capture date of the aerial imagery used in Stage 1 of the classification. 37% of Adelaide's urban area is permeable ground (plantable space) and 19.8% is impermeable surface (e.g. roads and pavement), and when combined with above ground impermeable surfaces (e.g. buildings), 44% of Adelaide's urban area is impermeable and would contribute to surface water accumulation. At the suburb scale (**Fig. 9**), the proportion of total suburb area that is plantable space, ranges from 78.0%% in Parafield (3,459,041 m^2 plantable space) to 6.4% in Mile End South (42,671 m^2 plantable space), with an average of 27% across all suburbs. The areas with the lowest proportions of plantable space are concentrated within a ~4.5 km radius of the Adelaide CBD (**Fig. 9**). Within the 2018 LIDAR survey area, the three land ownership categories that contribute the most to the total amount of plantable space are Private land (30.8%), State Government land (20.0%) and Local Government land (16.2%).

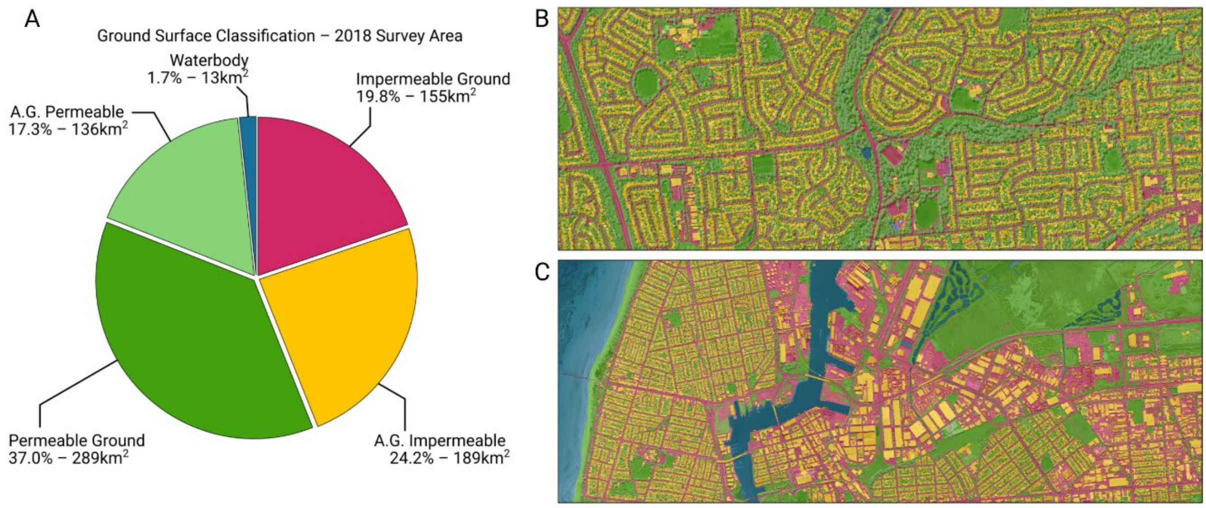


***Figure 8** – A: Statistical breakdown of the distribution of permeable (plantable space) and impermeable surfaces across the 2018 LIDAR survey extent. B: Example output of the classification from Redwood Park. C: Example of the classification from Port Adelaide and surrounds. Note: classification colour codes are constant across all three images. Modified from Holt (2021).*

4.4 Key Project Outcomes

Mapping the amount and spatial distribution of plantable space across the most heavily urbanized areas of metropolitan Adelaide provides much needed spatial and temporal context to the 2018/19 tree canopy benchmark and the value of the urban forest in certain areas.

By directly comparing the amount of tree canopy coverage within a suburb, as well as the proportion that suburb that is plantable, it is possible to understand the 'greening potential' of that suburb as well as the relative importance of preserving existing trees. **Figure 10** shows a bivariate plot of the proportion of plantable space versus the overall tree canopy cover for all suburbs wholly within the 2018 LIDAR survey area. Each of the four regions define the vulnerability and potential of the urban forest in each suburb. 'Ideal' suburbs have high tree canopy cover and high proportion of plantable space, meaning lots of existing trees and lots of space to plant more. 'High Greening Potential' suburbs have low tree canopy cover and high plantable space, i.e. few trees but ample space to plant more given effective planting strategies. 'At Risk' suburbs have high tree canopy cover, but very low proportion of plantable space, meaning that the existing trees need to be protected as there is little plantable space to replace trees lost to urban infill. Finally, 'Code Red' have low tree canopy cover and low plantable space. 76 suburbs are ideal, 151 suburbs have high greening potential, 44 suburbs are at risk and 38 suburbs are code red. It is these 38 suburbs that should be targeted in greening initiatives and policy development/reform as they have very few trees and very little space to plant more. Whatever the vulnerability or potential of the urban forest, private landowners will play a central role in the success of any planting initiatives given that the majority of plantable space resides on private land.

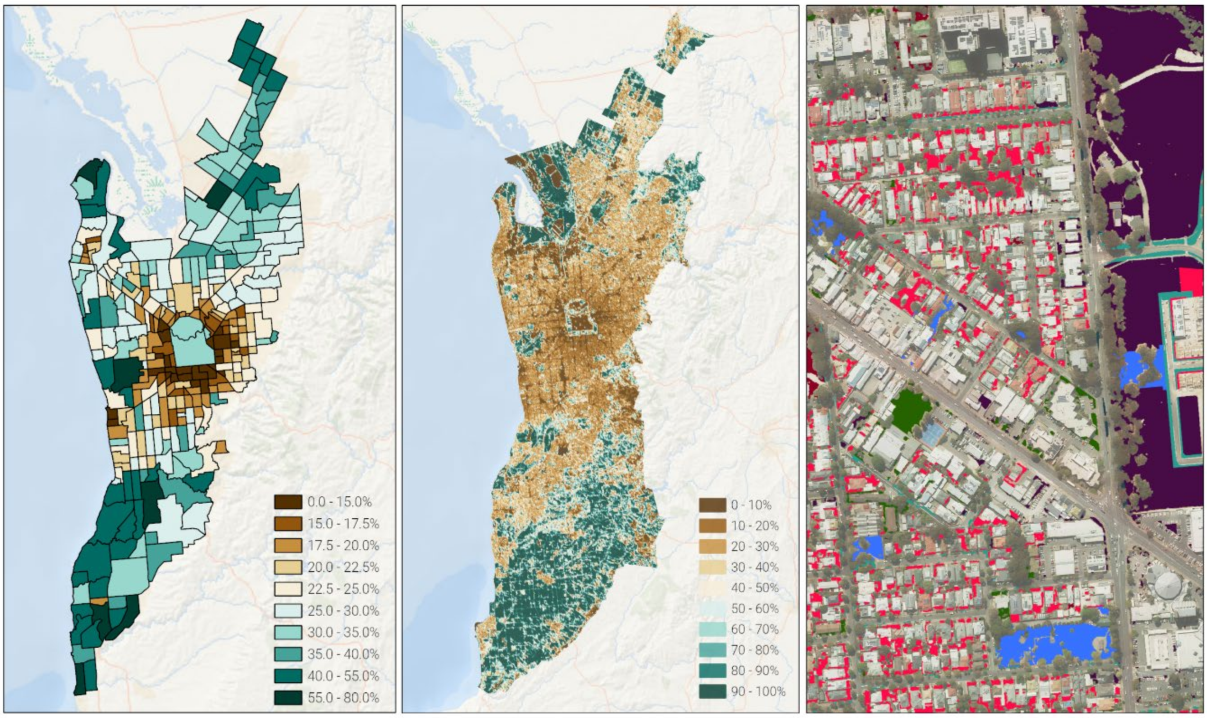


Figure 9 *– Left: The proportion of plantable space for each suburb wholly within the 2018 LIDAR survey extent. The suburbs with the lease amount of plantable space are concentrated in a 4.5km radius of the CBD. Centre: The proportion of plantable space per unit area (100m by 100m) across the 2018 LIDAR survey extent. Right: An example of plantable space classified by land ownership type, where red denotes Private Land, blue denotes Local Government land, light green denotes Local Government Road and dark green denotes Community Land. Left & Right Base-map: NWA, Geoscience Australia, Esri.*

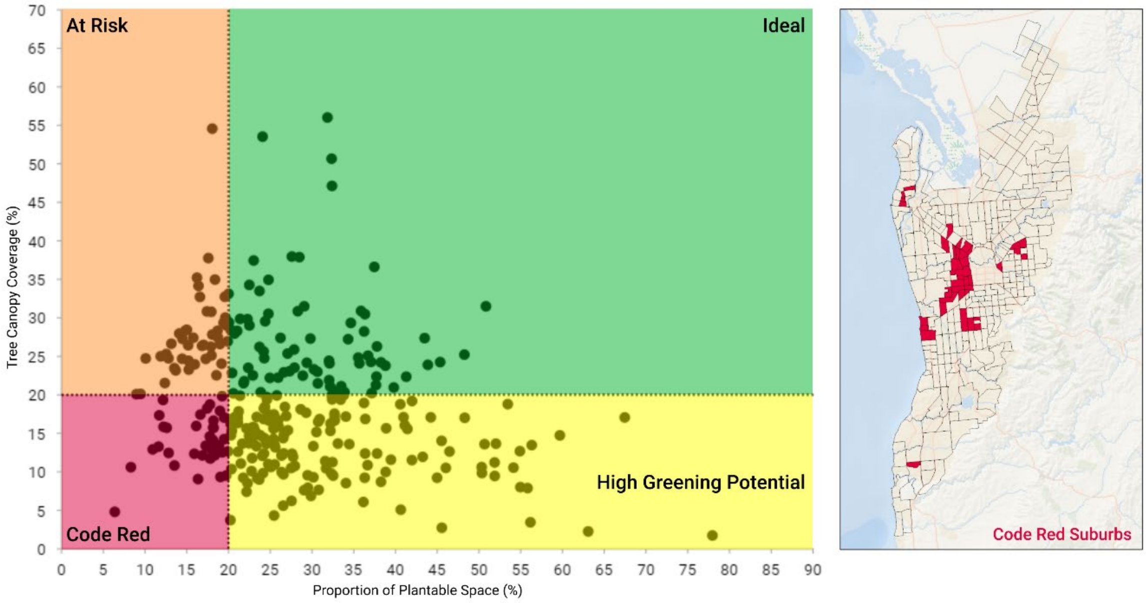


Figure 10 *– Left: A bivariate plot showing the proportion of each suburb that is plantable space, compared to the tree canopy coverage of that suburb. Right: a map showing the distribution of 'Code Red' suburbs. Right Base-map: NWA, Geoscience Australia, Esri*

5. Case Study 3 – High resolution tree canopy change detection and classification, City of Unley, 2018-2021

5.1 Project Summary

City of Unley commissioned Aerometrex to capture LIDAR across the LGA in April 2021 to produce a full urban forest assessment and provide an updated tree canopy coverage. This could be compared to the 2018 benchmark to quantitatively the measure the change in tree canopy cover over three years. A detailed investigation into the types of changes that were occurring to the tree canopy was used to gain a better understanding of what processes were contributing most to measured tree canopy gain and/or loss.

5.2 Methodology

All analyses used within the 2018/19 benchmark study were repeated, with the same input parameters and resolutions in order to produce datasets that were directly comparable to previous results. Additionally, Aerometrex utilised newly developed image segmentation and OBIA workflows to produce high-resolution (10cm) tree canopy coverage maps, for both the new 2021 LIDAR data and the historical 2018 dataset, to classify the changes occurring to the tree canopy across City of Unley. Isolated occurrences of tree canopy loss and gain were classified as Tree Planting and Tree Removal respectively. Areas of gain and loss greater than $4m^2$ and joined to an area of no-change (pre-existing tree canopy), were classified as Tree Growth and Pruning Reduction respectively. Areas of change less that $4m^2$ in area and joined to pre-existing canopy were left unclassified to remove noise associated with tree movement between and during captures. High resolution aerial imagery was used as a validation dataset and to provide an understanding of the changes in the urban environment that were driving tree canopy loss and gain. The spatial distribution of tree canopy losses and gains were assessed using standard and weighted hotspot analyses based on the Getis-Ord Gi* statistic (Ord and Getis, 1995; Getis and Ord, 2010).

5.3 Results

City of Unley Tree Canopy Cover

The repeat analysis of the urban forest across City of Unley showed that the average change in canopy height was 0.4m, the overall tree canopy coverage (measured at 1m resolution) has increased by 1.37% to 27.99% since 2018 and the largest increase by area in tree canopy coverage occurred in canopy between 3m to 10m in height.

As with the 2018 study, Residential and Private land contribute most to tree canopy cover. When measured at 10cm, the overall tree canopy coverage is refined by 4-5% for each epoch, 21.66% and 23.05% for 2018 and 2021 respectively, but critically the tree canopy change is +1.39%, only a 0.02% difference when compared to the 1m resolution dataset.

Tree Canopy Change Classification

Very high-resolution tree canopy maps for both epochs provided a robust comparison for the classification of tree canopy change (**Fig. 11**). Of the total gain in tree canopy cover, existing tree growth contributed five times the amount of new canopy (306,142 m^2) than newly planted trees reaching 3m in height (62,109 m^2), and solely offsets the total tree canopy loss, both by pruning reduction and tree removal (172,673 m^2 and 127,244 m^2 respectively). The average contribution of new tree canopy by a newly planted tree reaching 3m in height is 3.8 m^2 and the total area of increase due to tree planting is the equivalent of 16,344 new trees at 3m in height. The total contribution of existing tree growth and total canopy loss is the equivalent of 80,563 and 78,925 new trees at 3m in height respectively.

5.4 Key Project Outcomes

The effect of data resolution on greening target assessment

Comparisons between the overall tree canopy cover and change in tree canopy cover measured at two different resolutions (1m and 10cm) show that the value for the overall tree canopy coverage can be 4-5% larger when measured at coarser resolutions as compared to fine resolutions, however the change in tree canopy cover is constant, independent of resolution. These results indicate that the precise wording used when defining an LGA's greening target can have an effect on what resolution data is appropriate to assess that target. For example, greening targets such as "reaching 30% tree canopy cover by the year 2030" require high-resolution datasets which provide precise, refined tree canopy coverages. In comparison, greening targets such as "increasing tree canopy cover by 30% by the year 2030" can be assessed using coarser resolution datasets as the change over time is accurately measured regardless of resolution.

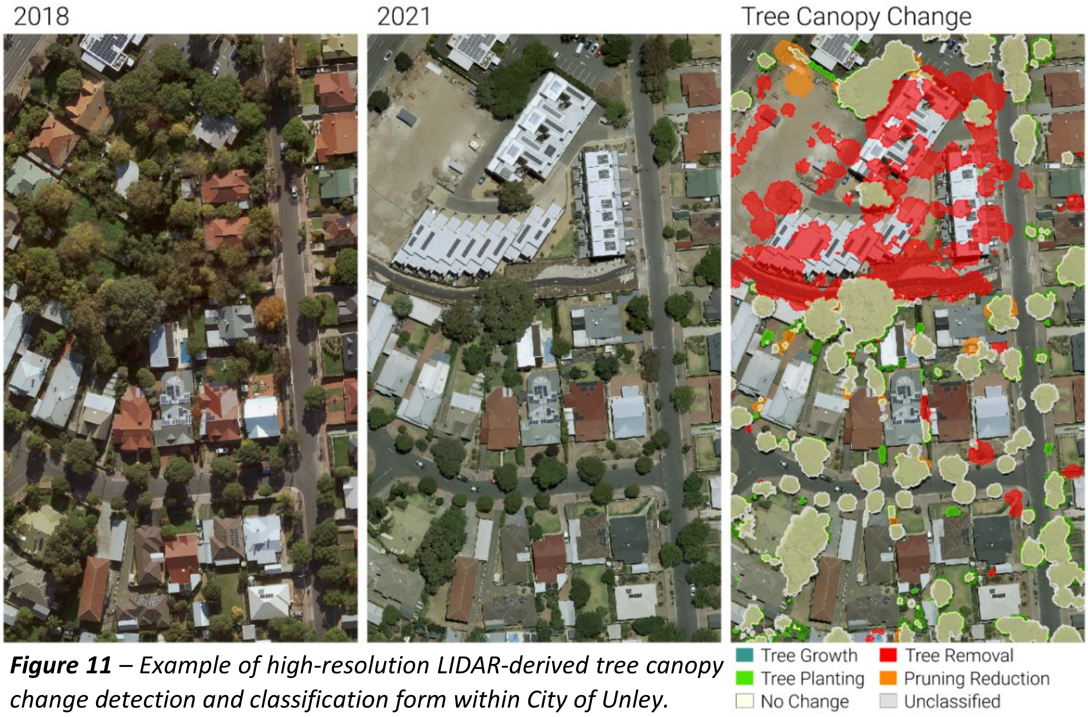


Figure 11 *– Example of high-resolution LIDAR-derived tree canopy change detection and classification form within City of Unley.*

Implications on Urban Forest management in City of Unley

The large-scale contribution of new tree canopy cover due to the growth of existing trees, as compared to newly planted trees, suggests that preserving and protecting existing trees is of critical importance alongside planting initiatives if City of Unley is going to continue to increase the amount of tree canopy coverage in the future.

The average area of tree canopy lost per tree removal is 11.8 m2, three times the average contribution of new canopy due to newly planted trees. This highlights the importance of protecting existing trees, because as the contribution of existing tree growth is reduced through tree removal, losses in tree canopy cover will rapidly outpace the contribution of newly planted trees. Weighted Hot Spot Analysis shows that the four most statistically significant clusters of large magnitude canopy loss occur at sites of urban development (Fig. 12). This would suggest that urban development and associated urban infill pose the greatest threat to the urban forest within the City of Unley.

6. Conclusions

The three case-studies presented here showcase the power of geospatial data such as Airborne LIDAR to produce city-wide urban forest assessments which quantify the amount and spatial distribution of both tree canopy cover and plantable space, as well as explicitly measuring and classifying tree canopy change with time, across both private and public land. City-wide LIDAR-derived tree canopy and plantable space studies provide critical spatial and temporal context to the process of valuing the urban forest, whether that value is defined by monetary value or socioeconomic benefits. Large-scale urban forest assessments will play an increasingly important role in helping environmental management experts and policy makers at all levels of government build greener, cooler, more sustainable cities and increase the community's resilience to the ongoing negative effects of climate change.

The results of each of these analyses highlight two critical considerations for environmental management experts across Adelaide:

1. Private landowners will play a critical role in helping build a greener, more sustainable future for Adelaide as the overwhelming majority of both existing tree canopy cover and available plantable space resides on privately owned land.
2. Preliminary tree canopy change detection and classification at the LGA level over the last three years following the 2018/19 benchmark suggests that growth of existing trees contributes a much larger amount of new tree canopy than newly planted trees. Given the time lag between planting and major tree canopy contribution, it is critical that local governments preserve existing tree canopy cover by protecting existing trees from urban developments and infill.

***Figure 12** – Aerial imagery from the location of the four most statistically significant clusters of large-scale tree canopy loss between 2018 and 2021 in City of Unley. For each image pair, the top image is captured in 2018 and the bottom is captured in 2021, with tree canopy loss vectors (both Pruning Reduction and Tree Removal) overlain in red. In each case the tree removal is associated with developments and urban infill.*

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