Attachment 2: Tree Ledger Report 2012-2022

City of Port Phillip Tree Ledger

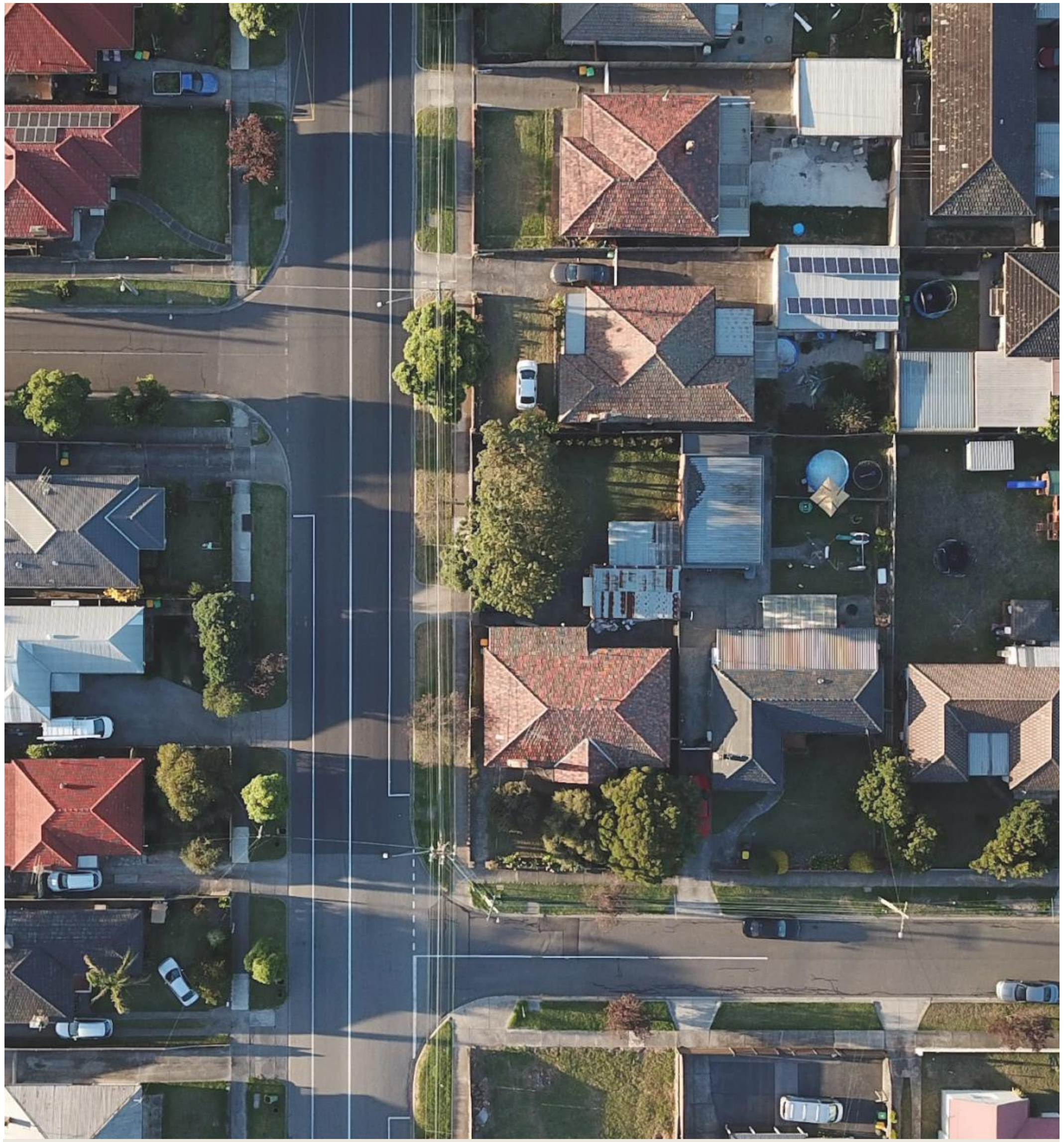
REPORT
2012-2022

+ Data Analytics
+ Insights
+ Modelling

26 May 2023

Prepared for the City of Port Phillip.

by Player Piano Data Analytics



Player Piano Data Analytics

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1. EXECUTIVE SUMMARY

The City of Port Phillip is currently in the process of formulating an urban forest strategy that will guide its efforts for greening until 2040. The city is seeking to gain a comprehensive understanding of the extent and condition of the tree canopy council wide and how it has changed since the implementation of the previous strategy in 2011.

Player Piano Data Analytics (PPDA) have been engaged to conduct a comprehensive assessment of both the existing and historic urban forest on private and public land from 2012-2022.

Urban forests are complex: trees grow at a rate that depends on local conditions, climate and rainfall. In cities, they also depend on human behaviour in that they are planted, maintained and sometimes eventually removed. PPDA measures these interactions utilising remote sensing and data science workflows and records the measurements in a database called Tree Ledger.

The Tree Ledger process translates trees visible in an aerial photograph into georeferenced polygonal outlines of individual canopies. Each tree is assigned a unique Tree ID, which links each corresponding observation temporally across the study period enabling the monitoring of growth and continued presence. Observations of tree canopies are then coupled with additional georeferenced data generated by remote sensors such as LiDAR, NIR (Near infrared) and thermal infrared.

A Tree Ledger has been constructed over the extent of the City of Port Phillip, using the councils inventory of Aerial Photography and LiDAR data.

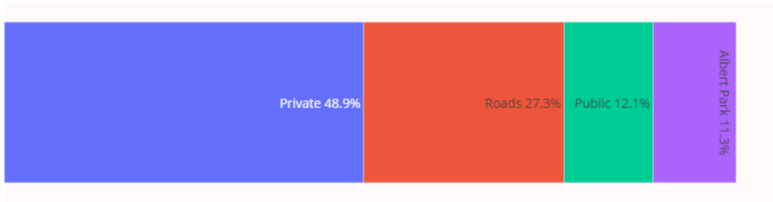
Furthermore, a thorough quality assurance process has been conducted by human analysts for observations made for 2022 to ensure CoPP has an accurate baseline of canopy cover.

This report presents high level insights derived from the CoPP tree ledger and details the methodology and process undertaken to build it.

The custodianship of individual trees has been estimated based on a model where the trunk of a tree is assumed to be the centroid of its canopy.

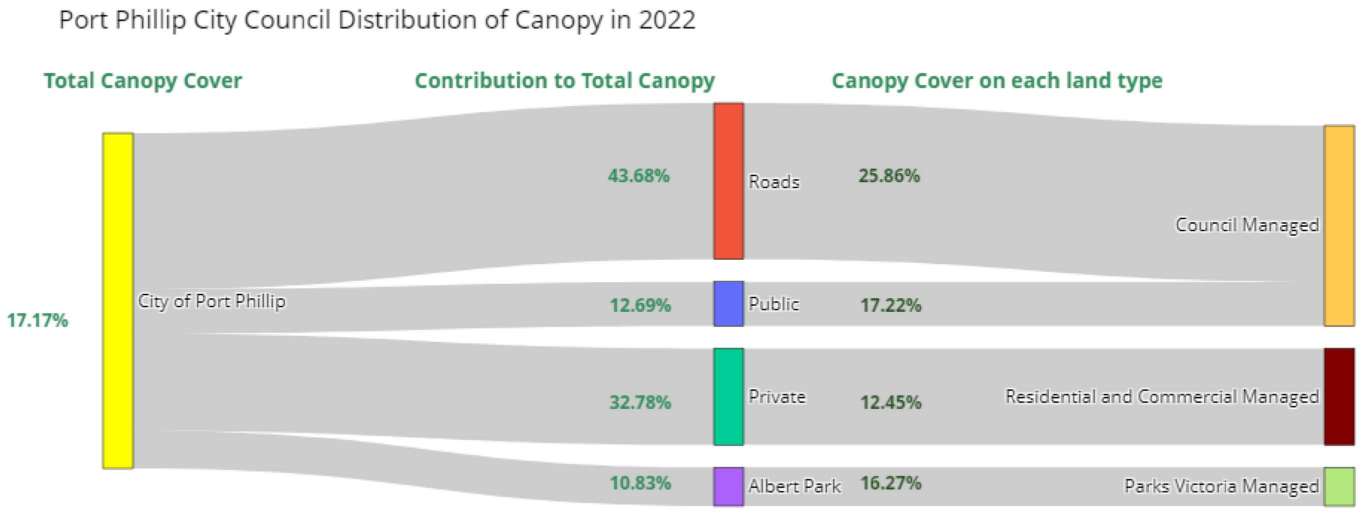
Each tree is categorised into the following categories. **Private** and **Public** uses. This classification represents two distinct types of human activity; Private residential and commercial premises, in contrast to areas accessible to the Public and/or managed by Council. **Roads** that encompass footpaths and nature strips, and **Albert** Park which is public space managed by Parks Victoria.

City of Port Phillip Distribution of Land Type



Privately owned land is the largest portion in the land break down conceptually it serves as the land use type with the most capacity to influence canopy cover.

CoPP has a larger portion of land that is Roads compared to other LGA's around Melbourne.



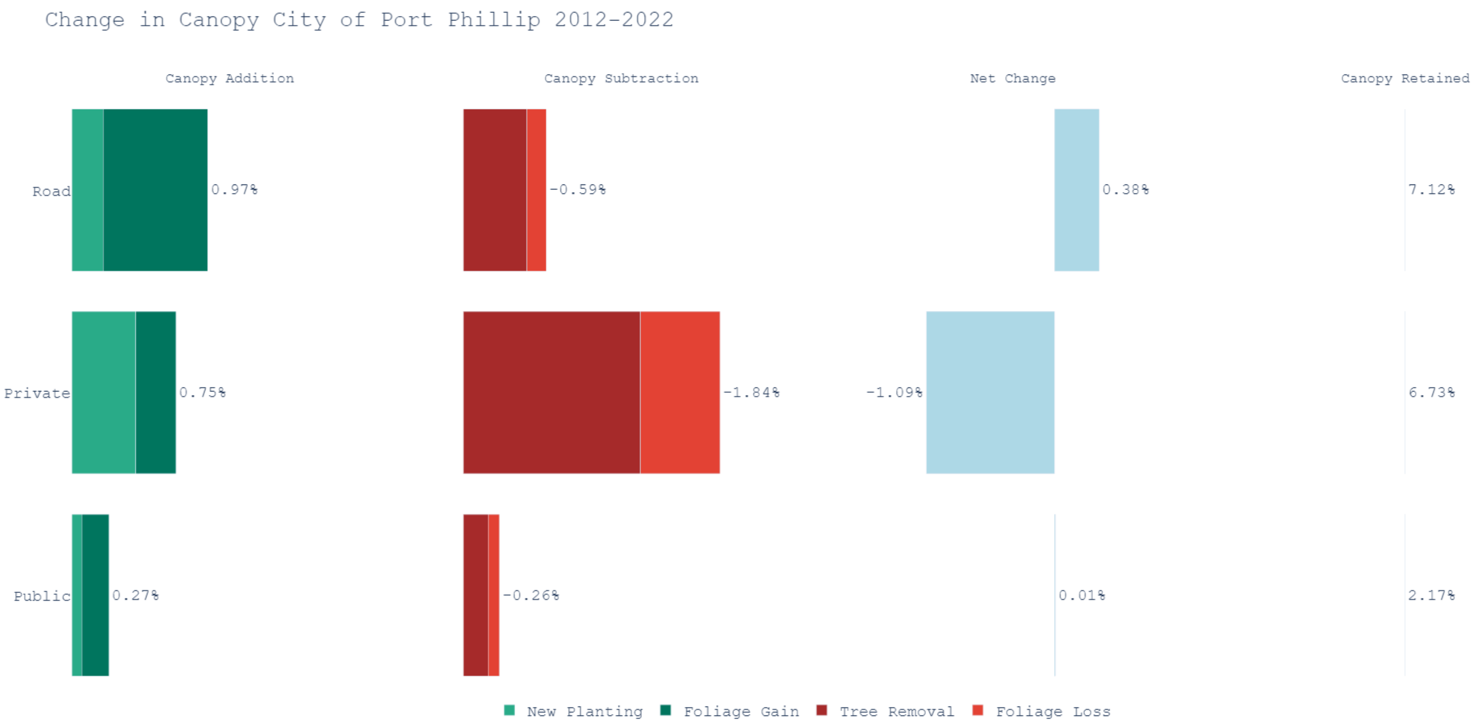
In 2022 **17.17%** of the extent of Port Phillip is covered by canopy from trees that are greater than 3m in height.

43% of the canopy cover can be attributed to Trees present in the **Roads** landuse type. It contributes an extra 2.3% canopy cover to the private realm. The canopy cover on roads is 25%, well above the average for inner city Melbourne making it a unique feature of CoPP urban forest.

The canopy cover within **Private** land is 12.45% and it contributes 32% to the total canopy cover.

Albert Park Reserve is the largest public space in CoPP. While it is managed by Parks Victoria it performs a crucial role in meeting open space and recreation needs of residents and provides vital green space. Albert Park Reserve has 16.27% canopy coverage and contributes 10.83% to the total canopy cover.

As Albert Park Reserve is not managed by Council, the area has been removed and overall canopy analysis results in the accompanying analysis booklet will report **Council Managed and Residential/Commercial Managed canopy**.

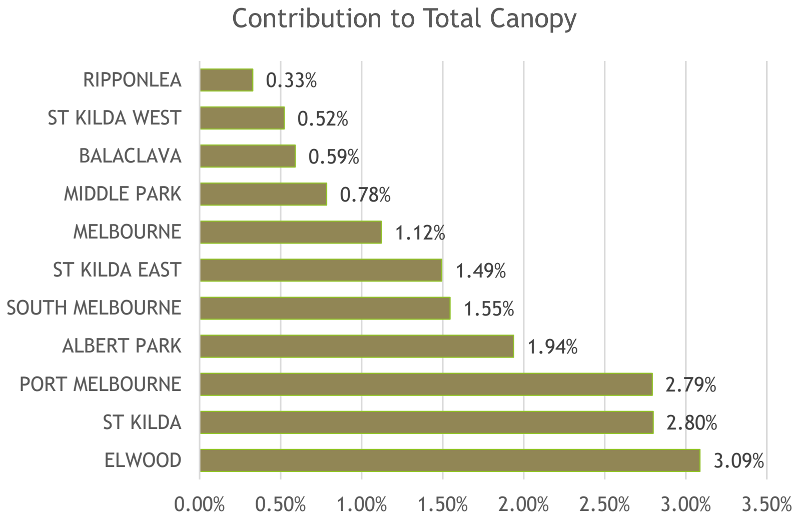


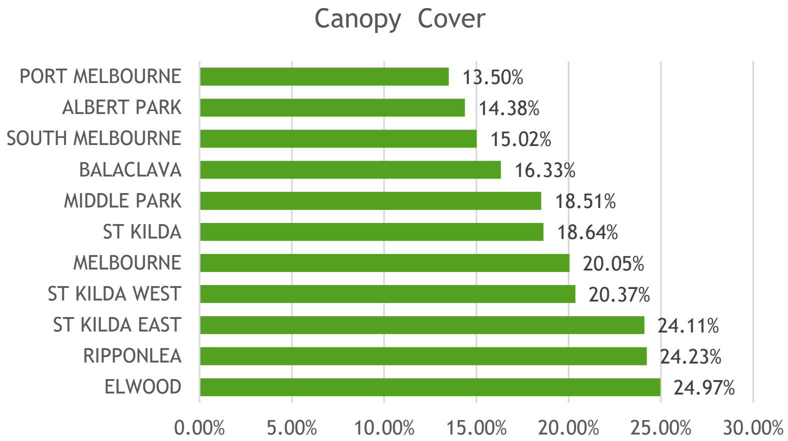
In summary, the majority of additional canopy in CoPP in 2022 is the result of existing trees on roads growing (Foliage Gain). It has offset the amount of foliage loss due to removal, natural loss and pruning. The change on Roads is an additional 0.38% Canopy cover.

The Private landuse has resulted in a negative net change of -1.09, which is predominately driven by removals of trees on private land.

On Public land canopy cover has not experienced significant change in canopy cover. Canopy cover from trees that were removed were ultimately offset by the growth of Trees.

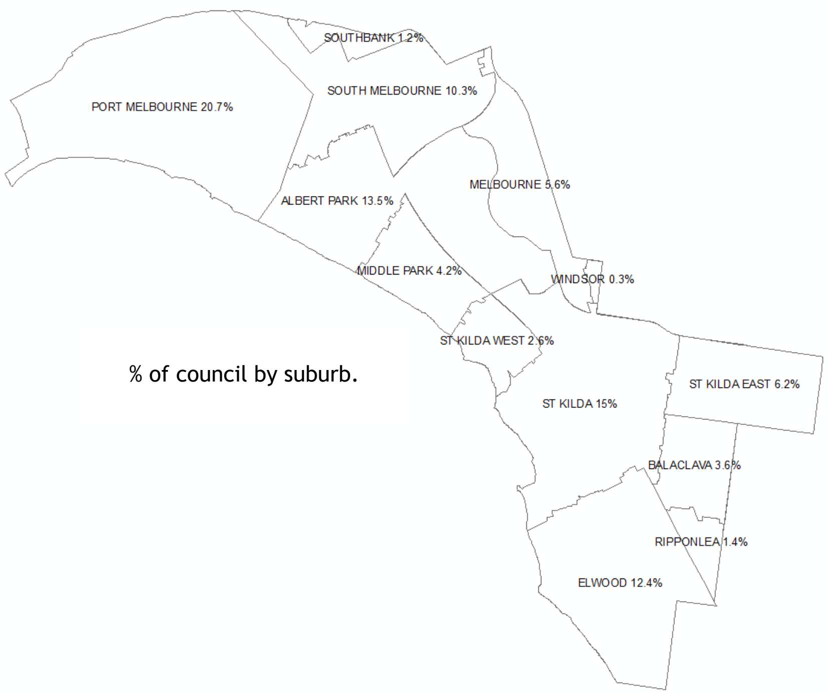
More than 50% of the additional canopy cover on private property can be accounted for by new plantings. As new plantings mature they may offset the removals that had taken place.



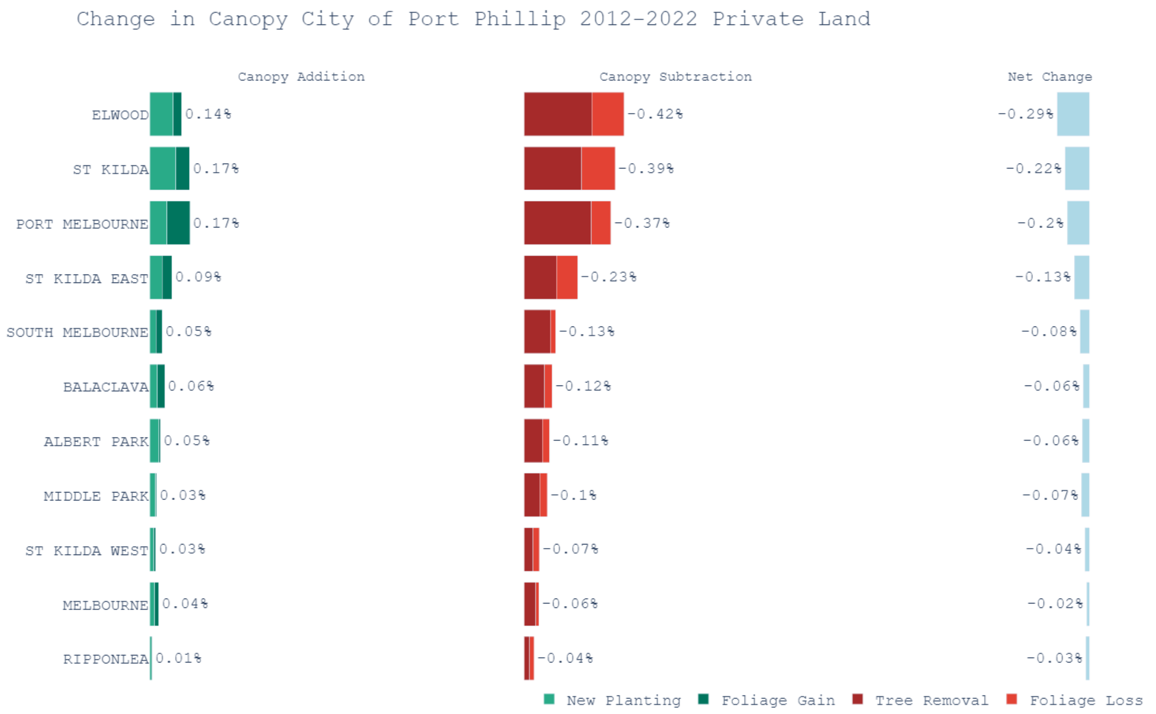


The canopy cover in CoPP varies regionally**, 61%** of COPP canopy cover is distributed amoungst three localities – **Port Melbourne, St Kilda and Elwood.**

Elwood, Ripponlea and St Kilda East have canopy cover above 24% which is exceptional for an inner city suburb.



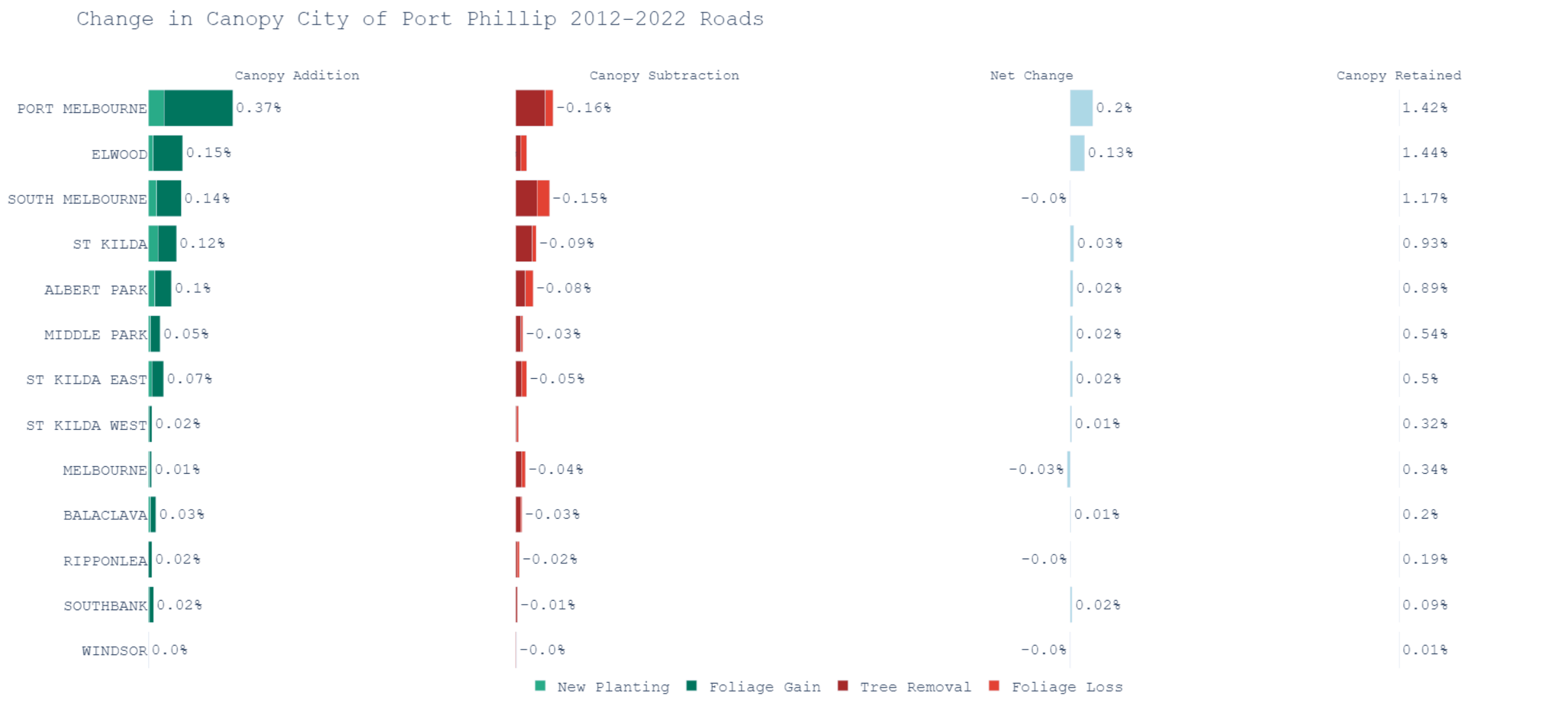
% of council by suburb.



Changes on Private properties is further explored by suburb to determine whether there is a particular region driving the trend or whether it a council wide trend.

All suburbs within Port Phillip City council are experiencing a net decline in canopy on private land.

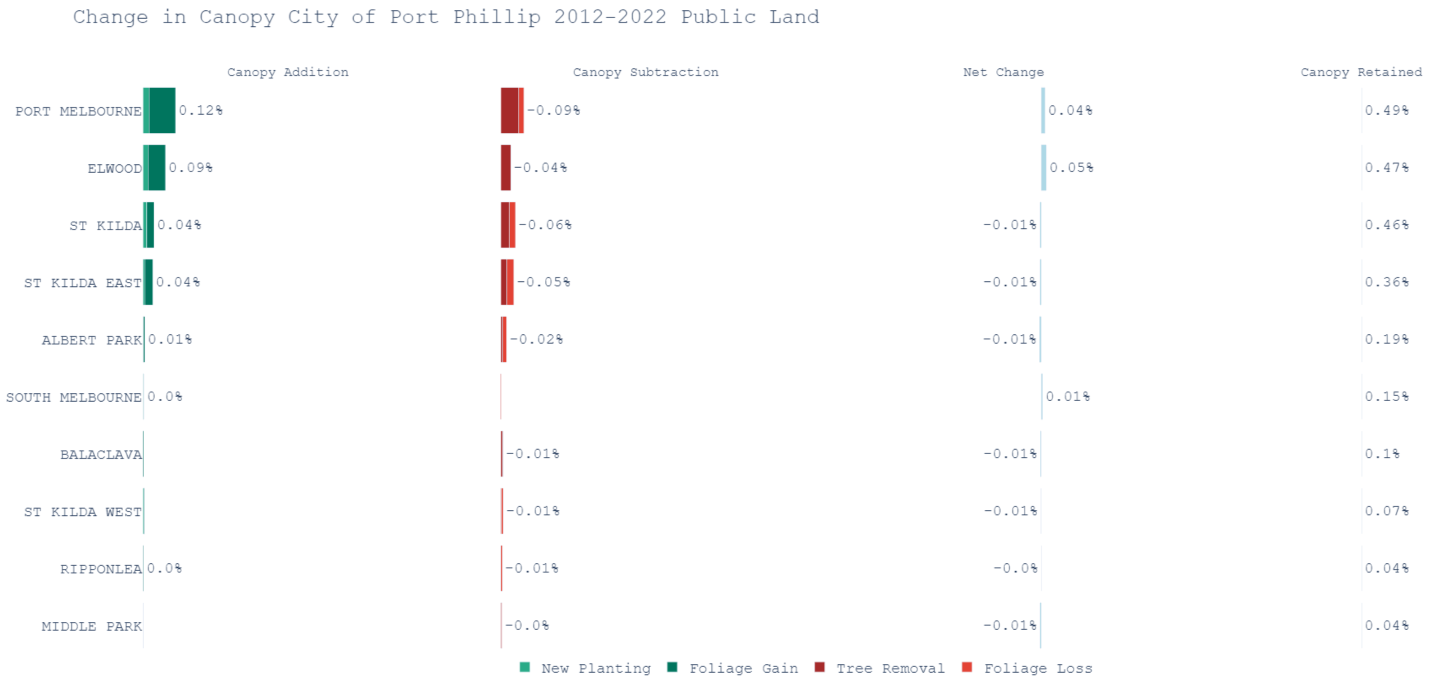
Elwood, St Kilda, St Kilda East and Port Melbourne show the greatest loss. These four suburbs also, contain 71% of all trees within private properties.



Changes on Roads is further explored by suburb to determine whether there is a particular region driving the trend or whether it a council wide trend.

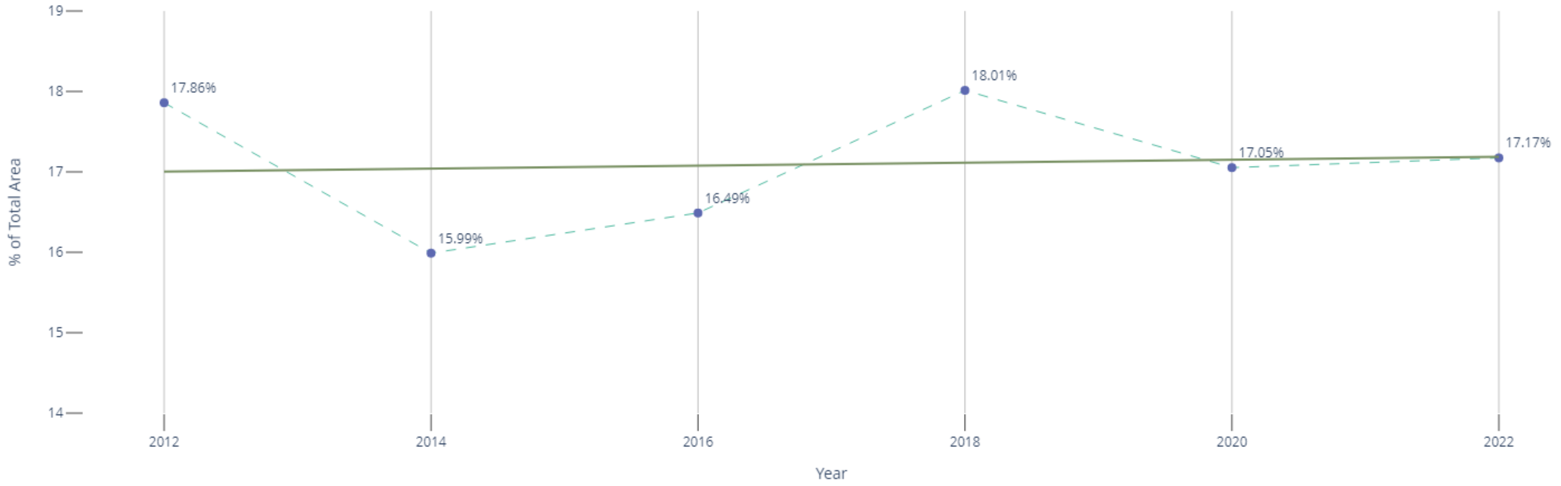
Growth of existing trees in Elwood, and Port Melbourne have made the largest contribution to the positive net change reported council wide.

82% of the additional canopy within the Roads landuse class can be attributed to these two suburbs.



Changes on Public Land is further explored by suburb to determine whether there is a particular region driving the trend or whether it a council wide trend.

Growth of existing trees in Elwood, and Port Melbourne have made the largest contribution to the positive net change reported council wide.



The canopy cover in Port Phillip in 2012 was 17.86%, in 10 years Port Phillip has experienced a decline of -0.69% in tree canopy.

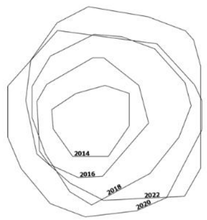
The trend of canopy cover change in Port Phillip is a slight decline driven mainly by removals on Private Property.

2. BACKGROUND

Largely influenced by the use of time lapse photography in phenological experiments that monitor plant growth. The concept of the Tree Ledger looks to make this kind of connection between aerial photography and the urban forest.

Aerial photographs within the local government inventories have been orthorectification, this ensures that pixels in an image are a reflection of their true position. Drawing a polygon over an individual tree crown within this imagery is equivalent to making a scientific observation around the size of the tree crown. If all these observations over a city are summed up they represent the total canopy cover of a city.

Similarly if a single observation of an individual tree were to be made across the full temporal collection of aerial photography it is turn possible to track when the tree was planted, and how it matured.



YEAR	Area (m²)
2014	10.4
2016	23.7
2018	46.9
2020	68.6
2022	69.1

A polygon is drawn over the same tree in 8 years of aerial photography.

Traditional methods of measuring tree crowns from aerial photography have relied on human interpretation of tree crowns to draw polygons and are currently still considered the most accurate approach. Measuring over 200,000 tree crowns on over 20 aerial photographs is an unattainable goal for humans given the constraints around time and budget.

The approach taken to build the Tree Ledger combines the traditional method of human interpretation with an ensemble of the latest innovations in deep learning models.

PPDA image analyst build a large amount of training data that fine tunes multiple models to accurately identify trees on a particular photograph. The process leads to cutting edge accuracy levels, and furthermore PPDA analysts look over the full extent of the council for the 2022 aerial capture removing noise and making corrections where necessary.

The Tree Ledger workflow aims to translate high resolution aerial photography into georeferenced observations of individual tree foliage or clustered tree foliage. This in turn generates a map of individual and clustered trees and enables us to monitor the presence of trees, and changes to their growth rates and canopy size over time.

3. PROJECT OBJECTIVES

To study the long-term trends in tree canopy coverage the following four project objectives were defined:

1. Build Tree Ledger

Human analysts generate a training/testing set. Train a model, extrapolate over full extent and integrate with LiDAR and nIR.

2. Image Analyst QA

Human analyst quality assure a single photograph generating a point of 'truth'

3. Urban Forest Modelling.

'Point of truth' coupled with historical trends are used to retrospectively correct sensor anomalies.

4. Analysis and Synthesis

Analyse canopy change based on landuse, height intervals, health condition and species by both precincts and council wide.

4. METHODOLOGY

The following methods were used to address the Project Objectives:

1. Data Exchange

Confirm project parameters and exchange of source photography, and LiDAR data with CoPP. Establish land use types and generate spatial layers.

2. Generate Training Data

Image analysts generate an AI training set based on project specifications. The training set includes areas of all different land use types and planting zones.

3. Feature Extraction

Calibrate the AI algorithm to achieve a high level of accuracy. Apply the algorithm to the Complete database of aerial photographs.

4. Quality Assurance

1 epoch of AI derived tree observations and its corresponding aerial photography are distributed to the image analysts for review. This validation process ensures that the highest level of accuracy and data confidence is achieved.

5. Compiling Tree Ledger

Tree canopy database is Compiled and post-processing algorithms are deployed to minimise AI errors. This database is then integrated with data from LiDAR surveys in order to attribute 3D height of the landscape features and plant-health information from NIR. Trees are categorised into classes based on per year presence and consecutive crown size change.

6. Data synthesis, analysis and sampling.

Tree Ledger data is analysed on a regional and council-wide scale to determine trends and insights.

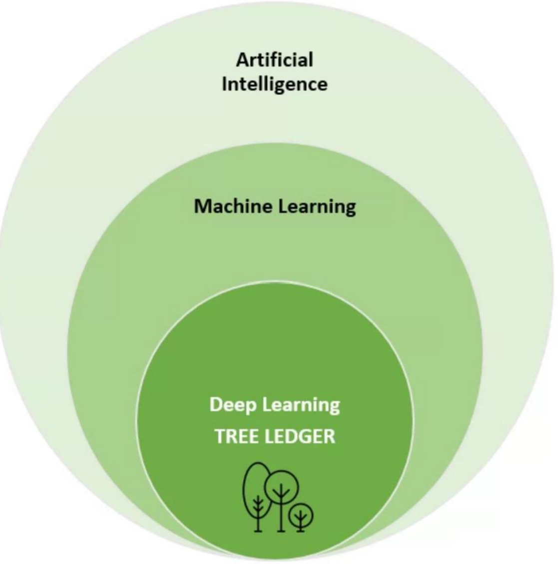
5. MACHINE LEARNING

To answer the Project Objectives, PPDA has used machine learning to map the presence of trees/vegetation across the study area using aerial photographs taken between 2012-2022.

Machine learning is an AI based mathematical modelling technique which leverages available data to improve the performance of algorithms and to make the most accurate predictions or decisions on datasets. It uses algorithms and mathematical models to analyse and draw inferences from patterns in data.

Deep learning is an area of machine learning where the pattern recognition capacity of the mathematical models is exponentially multiplied through the application of artificial neural networks, with linear equations numbering in the hundreds of millions. We use supervised deep learning to segment pixels in the photography and further machine learning to connect the target objects (eg: trees) over multiple photographs.

The main benefit of using machine learning is that tasks (such as recognising objects of interest within photography) can be automated allowing for the analysis much larger and complex datasets in comparison to the manual processes.



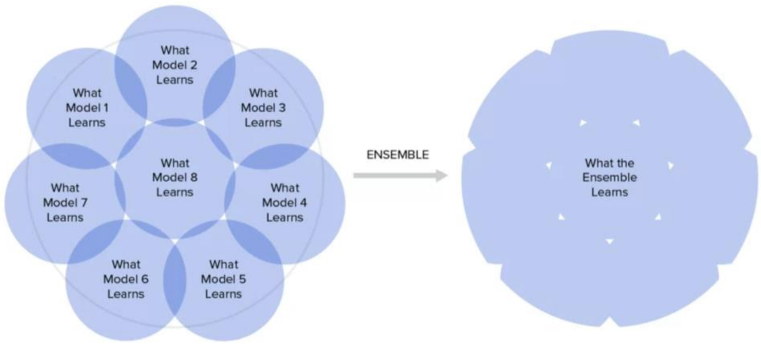
6. PLAYER PIANO DATA ANALYTICS

Player Piano Data Analytics (PPDA) specialise in feature detection from aerial photography using supervised machine learning. We build AI to monitor changes occurring in the urban environment, allowing our clients to plan for sustainable and climate resilient cities.

- **We deliver quality** – We believe AI can only be as smart as the people building it. Therefore, we are not just data scientists but also a team of 20+ local image analysts who train and verify the data.
- **We are experienced** having successfully delivered projects for local and state governments.
- **We put our clients in charge** by using their existing inventory of aerial photography, LiDAR, and NIR data. We work collaboratively with our clients and do not lay claim to the data derivatives.

PPDA's brand of machine learning is that good training data equals good machine learning. A highly accurate human derived training dataset will enable us to train multiple deep learning models, from which we will select and combine the best performing qualities of each. This is called an ensemble model.

In our experience, to achieve a reliable level of AI accuracy with minimal human intervention, around 5-7% of the total area needs to be covered by human derived training data. With this method we are able to build an ensemble AI advanced enough to confidently extrapolate what it has learnt to the remaining 93%-95% of the case study area.



7. MODEL DEVELOPMENT

Training/Testing Set Generation

City of Port Phillip supplied an inventory of aerial photographs of the study area. Only summer/spring photographs (ie: photographs captured in December, January, February or March flights) were used in the analysis to maintain seasonal consistency in tree canopy size. Due to the diversity of urban landscapes within CoPP a number of training sets were generated using different sample areas of residential and dense open space.

This approach ensured that algorithms were trained and calibrated to target the specific diversity and density of vegetation found within the case study area.

The number of samples used in algorithm training for the CoPP area:

50,736 samples covering the total area of 8.5 km2:

High resolution aerial photographs were divided into subsets of pictures representing a 250 × 250 m land area, thereafter referred to as tiles. A number of tiles (table) from each photograph were selected to create the training data. Photographs were inspected manually to ensure that the selection represented all urban forms and vegetation types characteristic for CoPP. The sample tiles were then randomly distributed to a team of Image Analysts who generated a training set from.

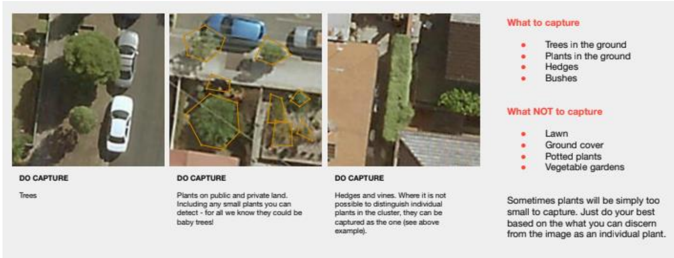
This study relied on LiDAR data to distinguish between a tree (> 3 m high) or a shrub (< 3 m high).

The following table shows the number of samples generated from each aerial photograph:

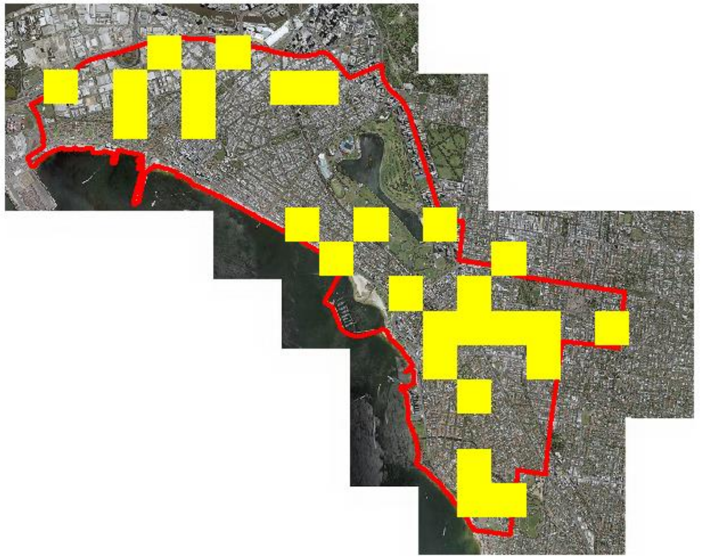
Year	Month	Resolution (cm)	No Samples	Canopy Area (m²)
2012	March	10	3,666	120,560
2014	Janruary	10	2,801	125,139
2016	Jan	10	2,570	91,066
2018	Feb	10	15,051	426,317
2020	Jan	10	8,264	350,064
2022	Feb	10	9,686	364,635
Total			42,038	1,477,785

The process of generating training data involved creating a clear set of rules that Image Analysts could all follow.

Online training sessions and written instructions specific to the project were given to the analysts. They were instructed to capture all types of vegetation as this study relies on LiDAR to evaluate whether vegetation is a tree (>3m) or a shrub (<3m).



Sample of training material distributed to Image Analysts.



2 Spatial distribution of training tiles across CoPP

Post Processing

Following the machine learning and ensemble modelling, mapped tree cover of the area undergoes post-processing. This process includes overlapping photographs of the same area from each consecutive year, in chronological order and grouping observations together in order to minimise noise and errors.

The following types of errors are minimised:

- Systematic photogrammetry errors, ortho-mosaic errors, white balancing, and blur.
- Cloud cover, shadowing and differing flight paths can make vegetation appear different in each photo.
- Classification error, machine learning errors because of insufficient samples in training data.

Tree Ledger uses the temporal scale per tree to minimise the above mentioned errors by filtering out vegetation that appears in one year but does not appear in other years or other inconsistent observations. This processing resulted in the rejection of approximately 1.5% of observations from every year included in the study.

Ensemble Model

A highly accurate human derived training set enables us to train multiple deep learning models, from which we will select and combine the best performing qualities of each. This is called an ensemble model.

In our experience, to achieve a reliable level of AI accuracy with minimal human intervention, around 5-7% of the total area needs to be covered by human derived training data.

With this method, we can build an ensemble AI advanced enough to confidently extrapolate what it has learnt to the remaining case study area.

We managed to generate training data over 12.3% of the area, enabling us to derive a final ensemble comprised of 4 models.

Quality Assessment

Once the deep learning algorithm has been applied to all aerial photographs, a representative dataset is distributed to the human analysts for quality assessment, including accuracy and consistency. The 2022 aerial photograph of the council area was parcelled into 500 ×500 m tiles with the predicted 2022 trees overlaid onto the corresponding aerial photography. The 2022 photograph was chosen for point of truth as it would provide council with highest confidence measurement of current urban forest,

Above: Extract from QA training data distributed

Analysts performing quality assessment reviewed all AI generated polygons over the entirety of City of Melbourne for the 2022 aerial photograph.

By establishing a 'point of truth' layer through trained human validation, we are able to gain a higher level of confidence in 2022 data and also a point of truth of existing foliage cover that we are then able to apply in Modelling as corrections.

LiDAR Integration

A LiDAR survey sourced from the State Government of Victoria's Coordinated Imagery Program (CIP) was incorporated into the algorithm and generated a georeferenced point cloud for 2017 & 2011.

LiDAR integration allows us to extract the corresponding points in the point cloud and overlays the two-dimensional (2D) geometry of each tree. The subsequent data is then split into deciles (see Figure 3) to create a 3D representation of each identified tree. We used the mean of all points in the 9th decile to provide a robust and high confidence height measurement of each tree. The 9th decile was used for the measurement because it is more robust than the highest point in any given point cloud (i.e. the 10th decile).

The 10th decile data points are frequently errors or outliers such (e.g. measurements performed on powerlines, birds).

3 Canopy profile derived from LiDAR. Vertical extent of the canopy is divided into 10 sections (deciles) and is attributed with its corresponding area (sqm). The height of the 9th decile is used to attribute tree height.

The 2018 LiDAR survey was used to attribute measurements made from 2011 to 2022.

We were unable to assign a height to measurements of trees removed prior to 2011, in lieu of this information we have made the assumption that any tree removed post prior to 2011 that had a crown area larger then 10 square meters is assumed to be above 3m.

NIR Integration

NDVI (Normalized Difference Vegetation Index) is a measure of the health of vegetation. It is calculated by taking the difference between the near-infrared and red bands of a remote sensing image, and then normalizing that difference by the sum of the near-infrared and red bands.

NDVI values range from -1 to 1, with values close to 1 indicating healthy vegetation and values close to -1 indicating little or no vegetation. NDVI is CoPPmonly used as an indicator of tree health because it correlates with the amount of chlorophyll in a plant, which is an indicator of its overall health and vigor.

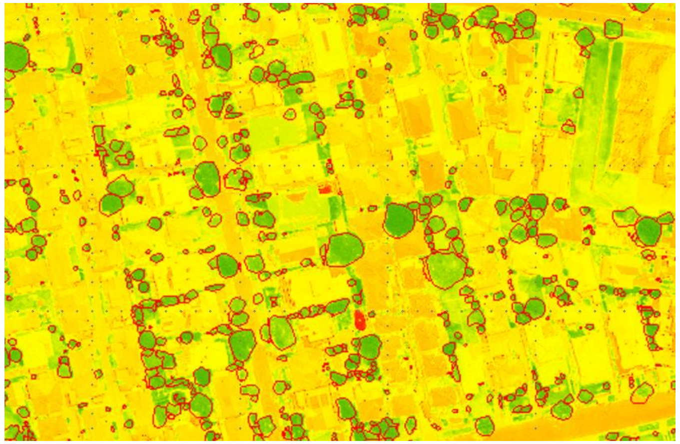
NDVI values can be used to monitor changes in tree health over time, and can also be used to detect areas of stress or disease in a forest.

CoPP provided NIR photographs for 2022. The aerial photography was then converted into an nDVI mosaic in which a single pixel represented an nDVI index.

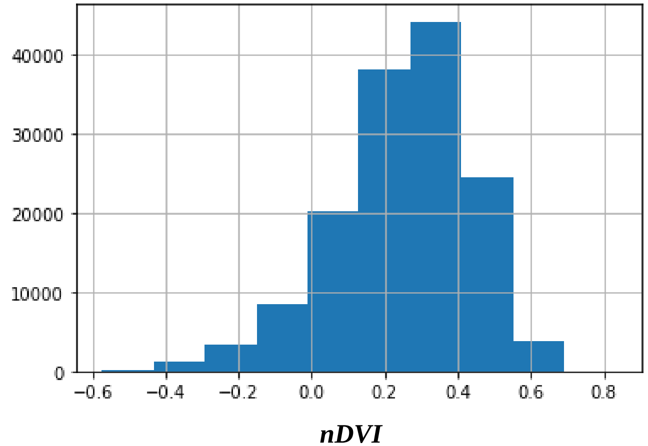
The individual tree polygon corresponding to a specific year is overlaid onto the nDVI mosaic and an average nDVI value is assigned to the treeID representing a specific year.

NDVI is more useful when there is more than one image for comparison, to see the change over time. The inclusion of this data at this stage means that this comparison can be completed when another capture is made.

Also, some species, for example, eucalypts tend to measure low nDVI values. Lower nDVI values could be attributed to a species specific attribute rather than a measurement of health.



For the purposes of the analytics conducted as part of this study we made a classification of health based on the frequency of nDVI scores.



Based on the nDVI frequency table we made the following classification.

nDVI Range.	Classification.
0.2 - 0.4 nDVI	Average Health
0.4 + nDVI	Above Average Health
- 0.2 nDVI	Below Average Health

Land Use Types

Mapped data has been aggregated to GIS layers that stratify land use into **Private, Public and Road** uses. This classification represents two distinct types of human activity; Private residential and CoPPmercial premises, in contrast to areas accessible to the Public and/or managed by Council.

Intersect Method

Analysis has been conducted using the "intersect" method to calculate how trees are contributing cooling to private and public land.

This means that a single tree can contribute cooling to multiple land-use types (ie: a large street tree can contribute to cooling on private land and vice versa)

This differs from a tree "centroid" approach, where the centroid/assumed trunk of a tree contributes only to the land use type that the centroid falls on.
The "intersect" approach was selected for this study in consultation with CoPP.

Above: "Intersect" method of analysis used to attribute vegetation and shade to public or private land.

8. Tree Ledger Classifications

Tree Ledger labels individual tree records into the following categories based on information it can ascertain from the temporal record as demonstrated in the figure below.

Foliage Gain/Loss is a 2D increase or decrease of canopy attributed to an individual tree.

14.3m² 19.6m² 36.9m² 52.7m² 68.1m²

Removals/Deaths represent the complete removal or death of a tree from a set year.

2014 / 86.3m² 2016 / 50.2m² 2018 / 62.5m² 2020 / 88.3m² 2022 / -- m²

New Plantings are complete new observations from a set year.

2014 / --m² 2016 / 2.4m² 2018 / 9.2m² 2020 - 14.6m² 2022 - 13.2m²

Using the information we have created a classification scheme which is used to track the driver behind canopy change. Each individual tree or tree cluster has been classified as…

Foliage Gain is a 2D increase of canopy attributed to an individual tree or cluster of trees. These records are categorised as 'gain' when there is a year-on-year increase >1.5% of the preceding detected size.

Foliage Loss is a 2D decrease in canopy area and can be associated to a number of factors including the natural senescence, limb drop, dieback and/or pruning. These records are categorised as 'loss' when a year-on-year decrease of -1.5% is detected.

Removals/Deaths represent the complete removal or death (no foliage) of a tree from a set year. In the case of the proposal, this is vegetation that had been detected in the 2014 photography but is not present in any of the following years.

New Plantings are complete new observations from a set year. In the case of the proposal, this is vegetation that had not been detected in 2014 but is consistently present in at least 2 subsequent photos.

9. PROJECT ACCURACY

For machine learning projects accuracy is measured by comparing the predictions of an algorithm versus the predictions of a human.

The following section describes the process to attain an overall level of the final model versus human delineations.

Training Data

The training data was split into subsets for training, testing and evaluating. The training data was used to train a state-of-the-art machine learning algorithm and each epoch of training is then tested on a sample set. The final accuracy of the study was assessed against the evaluation dataset.

The following table shows sqm coverage for each of the training/testing/evaluation datasets.

	City of Melbourne
Training	74,628,000
Testing	21,924,000
Evaluation	13,140,000
Total (sqm)	**109,692,000**

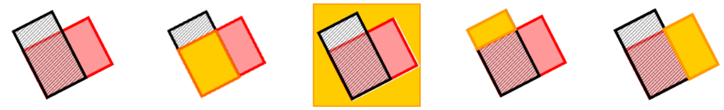
Evaluation

The evaluation dataset consists of human delineated features that were not used for training or testing when generating the ensemble model. To evaluate the precision and accuracy of the analysis, the human delineated data is compared with the final AI output.

The metrics we have used for evaluating accuracy are standard practice within computer vision projects.

For classification tasks (such as identifying trees from aerial photography), the terms *true positives*, *true negatives*, *false positives*, and *false negatives* are used to compare the results.

The terms *positive* and *negative* refer to the AI prediction, and the terms *true* and *false* refer to whether the AI prediction agrees with human judgment.



(a) Detection example (b) True positive (c) True negative (d) False positive (e) False negative

Legend: Reference building Detected as building Cases

These metrics can be broadly classified into two families. **Hit** and **Miss Rate** refer to amount of object detection. While the metrics of **Precision**, **Recall** and **Accuracy** refer to how well the objects have been detected.

Hit Rate: The rate at which human detected features are also detected by AI Model.

Miss Rate: The rate at which human detected features are not detected by AI Model.

Precision: % of pixels identified by humans that the model has classified correctly.

Recall: % of pixels identified by the model that the human has also identified.

Accuracy: A combination of all metrics.

Trees/Vegetation Accuracy Evaluation

	CoPP
Hit Rate	97.2%
Miss Rate	2.1%
Precision	92.2%
Recall	87.6%
Accuracy	96.4%

Summary

- The AI model is consistent with human performance when it comes to detecting pixels with tree on the photography as evidenced by the Hit and Miss Rate.
- When comparing the individual delineations, humans over estimate only slightly the size of a tree crown compared to the machine. This is shown by the lower recall value.
- The accuracy achieved this dataset is inline with cutting edge accuracy reported in machine learning tasks.

It should be noted that in image recognition tasks (such as we have conducted for trees), human accuracy is typically measured in scientific literature at 95%.