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Remote sensing and machine learning applications for urban forest biosecurity surveillance (PBSF030)

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Contents

1. Executive Summary **4**

2. Introduction **4**

3. Aim **6**

4. Methods **6**

4.1. Study area 6

4.2. Aerial image acquisition and processing 7

4.3. Ground truth data 8

4.4. Machine learning CNN models 8

4.5. Accuracy assessment 10

5. Results **10**

5.1. Classification accuracy 10

6. Discussion and Conclusion **11**

Conclusion 15

7. Recommendations **15**

9. Appendices, References, Publications etc. **15**

Acknowledgements 15

Author statement 15

Conflict of interest 16

Funding 16

Publications 16

References 16

1. Executive Summary

Urban and peri-urban trees in major cities provide a gateway for exotic pests and diseases (hereafter "pests") to establish and spread into new countries. Consequently, they can be used as sentinels for early detection of exotic pests that could threaten commercial, environmental and amenity forests. Post-border biosecurity surveillance for the early detection of exotic forest pests relies on monitoring of host trees — or sentinel trees — around high-risk sites, such as airports and seaports. In the event of an exotic pest incursion, surveillance of all known hosts in a defined area is necessary to determine whether eradication is feasible, and if so, was it subsequently successful. However, in Australia, there are few publicly available spatial databases of urban street and park trees, so locating and mapping host trees is primarily conducted via ground surveys. This is time-consuming and resource-intensive, and generally does not provide complete coverage. Advances in remote sensing technologies and machine learning provide an opportunity for semi-automation of tree species mapping to assist in biosecurity surveillance. In this study, we obtained high resolution (≥12 cm), 10-band, multispectral imagery using the ArborCam™ system mounted to a fixed-wing aircraft over Bayside Council in Sydney, Australia, which encompasses Port Botany and Sydney International Airport — two major entry pathways for invasion of exotic pests. We mapped 630 *Pinus* trees and 439 *Platanus* trees on-foot, validating their exact location on the airborne imagery using an in-field mapping app. These genera were chosen as they are hosts for several high priority pests for Australia. Using a machine learning, convolutional neural network workflow, we were able to classify the two target genera with a high level of accuracy in a complex urban landscape. Overall accuracy was 92.1% for *Pinus* and 95.2% for *Platanus*, precision (user's accuracy) ranged from 61.3% to 77.6%, sensitivity (producer's accuracy) ranged from 92.7% to 95.2%, and F1-score ranged from 74.6% to 84.4%. Our study validates the potential for using ArborCam imagery and machine learning to assist in tree biosecurity surveillance. We encourage biosecurity agencies to consider greater use of this technology.

2. Introduction

Trees form a major component of urban green spaces, providing multiple benefits, such as improving physical and mental health, filtering pollutants, regulating water flow and improving water quality, increasing urban biodiversity, and mitigating the urban heat-island effect (Alvey 2006; Novak et al. 2006; Armson et al. 2012; FAO 2016; Donavan 2017). Across the world, there has been a concerted effort to increase tree canopy cover in urban areas to facilitate these benefits and to mitigate against climate change (e.g., California Natural Resources Agency 2021; City of Sydney 2021; Greater London Authority 2021). The bulk of international trade, travel and mail arrives at seaports and airports in major cities. Global trade is recognised as a major mechanism for exotic species invasions (Haack 2006; Liebhold et al. 2006; Hulme 2009), with entry of invasive alien species predominantly through urban areas (Hulme 2009; Colunga-Garcia et al. 2010; Liebhold et al. 2016; Paap et al. 2017). Urban and peri-urban trees provide a resource and a habitat for invasive forest pests, and act as bridgeheads for the establishment and spread of exotic pests into new countries (Lombaert et al. 2010; Paap et al. 2017). There are numerous examples of exotic forest pests arriving and establishing in urban areas, including *Anoplophora glabripennis* (Motschulsky) (Dodds and Orwig 2011) and *Agrilus planipennis* Fairmaire (Siegert et al. 2014) in the United States, *Phytophthora ramorum* Werres, De Cock & Man in't Veld (Brasier et al. 2004) and *Hymenoscyphus fraxineus* (T. Kowalski) Baral, Queloz & Hosoya (Mitchell et al. 2014) in the United Kingdom, *Ophiostoma novo-ulmi* Brasier in New Zealand (Ganely and Bulman 2016), *Ceratocystis platani* (Walter) Engelbrecht & T.C. Harr. in Europe (Engelbrecht et al. 2014) and *Euwallacea fornicatus* Hopkins in South Africa (Paap et al. 2018).

Biosecurity agencies can use this convergence of trade pathways and urban areas to their advantage. Urban and peri-urban trees can act as sentinels for early detection of exotic pests (Wylie et al. 2008; Smith et al. 2010; Hulbert et al. 2017; Paap et al 2017; Mansfield et al. 2019; Wondafrash et al. 2021). Sentinel trees located around high-risk sites for arrival of exotic pests — e.g., proximity to trade and tourism entry points — can be monitored for symptoms or presence of pests to assist in early detection of exotic pests. It has long been recognised that conducting surveillance in urban and peri-urban forests near likely pest-entry points — high-risk site surveillance — is an efficient and effective means of early detection of exotic pests (Carter 1989; Wylie et al. 2008; Magarey et al. 2009).

Post-border surveillance for early detection of forest pests in Australia includes establishment of insect traps and host-tree surveillance around high-risk sites (e.g., major ports) as part of specific surveillance (Wylie et al. 2008; Bashford 2012), and stakeholder engagement (e.g., training of arborists and local council staff) as part of general surveillance (Carnegie et al. 2022; Department of Primary Industries 2022). Host-tree surveillance (sentinel tree surveillance) involves locating and mapping tree species that are key hosts of identified exotic forest pests, then visually assessing these for signs and symptoms of pest attack or pathogen infection. In the event of a detection of an exotic pest, host-tree surveillance in a defined area is a key component of delineating the distribution of the pest to ascertain whether eradication is feasible. If eradication is deemed feasible, an exhaustive detection of hosts is needed (Liebhold and Kean 2019; Pearse et al. 2021) for destruction of infected hosts (host-removal) or pest/pathogen control, then continued monitoring of hosts to ensure eradication success.

There are, however, very few publicly available spatial databases of urban street and park trees globally (Bennett 2020). In Australia, for example, most State-capital cities (i.e., Sydney, Brisbane, Perth, Hobart and Canberra) have publicly available street tree data for only one or two local government areas, with Melbourne the only city whose street-tree data covers most of its metropolitan area (Smith et al. 2010; Bennett 2020; Supplementary Figure 1). Additionally, many local government areas in Australia do not have georeferenced data on the locations or species composition of trees in public or private land within their administrative area. As such, locating and mapping host trees for post-border biosecurity surveillance, or during an emergency response to an exotic pest invasion, is conducted via ground surveys; generally using publicly available imagery to identify urban green spaces with many trees and then conducting vehicle and foot patrols to locate, identify and map individual tree species. This is time-consuming, labour-intensive, generally covers a limited spatial extent and provides incomplete detection of trees within an area. During the *Marchellina hellenica* (Gennadius) response in Victoria more than 85,000 pine trees were mapped, most via ground patrols (D. Smith, pers. comm.). There is an urgent need for a more efficient means of identifying and mapping tree species for biosecurity surveillance in urban landscapes.

Advances in remote sensing technologies has seen an exponential increase in studies on tree species classification (Fassnacht et al. 2016) and mapping of urban green spaces (Shahtahmassebi et al. 2021) using satellites, aircraft, and uncrewed aerial vehicles (UAVs). Optical sensors evaluated have mostly focused on high spatial resolution satellites (e.g., QuickBird, WorldView), and red-green-blue (RGB) cameras or multispectral and hyperspectral systems for aircraft and UAVs (Li et al. 2015; Odini et al. 2016; Jombo et al. 2020; Onishi and Ise 2021). The fusion of hyperspectral imagery with LiDAR (light detection and ranging) has also proven to be very successful at accurately delineating and classifying individual tree species in urban landscapes (Dian et al. 2016; Fassnacht et al. 2016; Liu et al. 2017; Wang et al. 2019; Shahtahmassebi et al. 2021). Important data that when combined have enabled accurate tree species classification include spectral data (e.g., spectra correlating to chlorophyll content), textural or structural data (e.g., leaf and branch density, angular distribution, clumping), along with an understanding of individual tree species phenology (e.g., flowering time, leaf senescence) (Fassnacht et al. 2016; Lui et al. 2017; Pearse et al. 2021).

Recently, significant advances have been made in the analysis of high spatial resolution imagery through the application of artificial intelligence and machine learning, in particular the application of deep learning techniques such as the use of convolutional neural networks (CNNs) which arose within the research field of computer vision (Onishi and Ise 2021). CNNs are a suite of deep learning algorithms that are specifically designed to analyse spatial patterns and provides an end-to-end learning approach that provide segmentation and classification (Hu et al. 2015; Liu et al. 2018). Recently CNNs have been very successfully applied to detect tree crowns using high spatial resolution imagery to locate and classify tree species (Lobo Torres et al. 2020; Schiefer et al. 2020; Braga et al. 2021; Lumnitz et al. 2021; Martins et al. 2021; Onishi and Ise 2021; Pearse et al. 2021).

3. Aim

In this study, we demonstrated the capacity of high spatial resolution, multispectral airborne imagery and the use of deep learning CNNs to locate and segment individual tree crowns and classify them as one of two tree genera within an heterogenous urban environment in the Australian context. Our intent was to illustrate the effectiveness of the application of such methodology to increase efficiencies, spatial areas covered and accuracy in locating and mapping of tree hosts of exotic pests for use in biosecurity surveillance.

4. Methods

4.1. Study area

The study area was the local government area of Bayside Council (~5,700 ha) in Sydney, New South Wales, Australia (33° 56’50” S, 151° 11’ 55” E) (Fig. 1). This area was selected because it falls within one of the main high-risk site surveillance zones of the NSW Department of Primary Industries’ Forest Biosecurity Surveillance Program (Department of Primary Industries 2022). This zone is centred around the Port Botany shipping terminal and encompasses Sydney International Airport and is recognised as a high risk for the entry and establishment of invasive forest pests, with forest biosecurity surveillance being conducted since 2014. High-risk site surveillance here includes insect trapping and surveillance of sentinel trees (Carnegie et al. 2018; Carnegie et al. 2022), primarily focusing on *Pinus* and *Platanus*. These two genera were chosen as targets for sentinel-tree surveillance as they are hosts for high priority tree pests for Australia, including 20 invasive species of biosecurity concern for multiple plant industries as well as environmental and amenity trees (Supplementary Table 1). Both genera are exotic to Australia, with *Pinus* spp. being evergreen conifers and *Platanus* spp. deciduous hardwoods. There is a broad heterogenous mix of other exotic and native tree genera within Bayside Council.

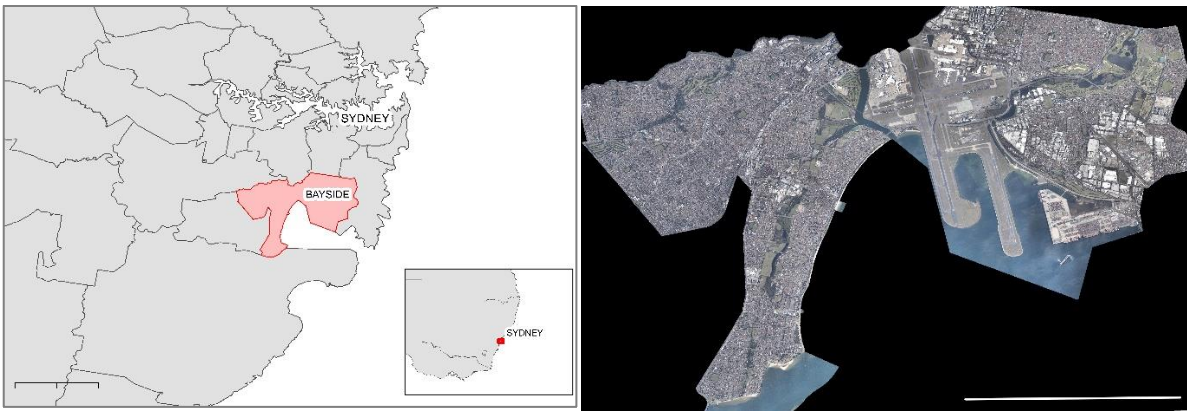

Figure 1. Study area: Bayside Council, Sydney, Australia. Scale = 5 km.

4.2. Aerial image acquisition and processing

Imagery was acquired using the ArborCam™[1] multispectral camera from a fixed-wing aircraft at 3,650 m above ground level in cloudless conditions between the hours of 14:15 and 16:30 on 10th November 2020. The timing of image capture was in late spring when *Platanus* trees in Sydney have full leaf canopies; by late summer to early autumn, leaves of *Platanus* begin to discolour. Imagery was acquired with sufficient overlap to produce a detailed Digital Surface Model (DSM) of the area to enable calculation of vegetation height. The ground sample distance (GSD) of the acquired imagery ranged from 12 cm (RGB sensor) to 36 cm (multispectral sensors). The ArborCam multispectral camera has seven narrow band (≤ +/- 10 nm full width half maximum) sensors centred at the following wavelengths: 450 nm (blue), 530 nm (green), 570 nm (orange), 655 nm (red 1), 680 nm (red 2), 720 nm (red-edge), and 780 nm (near infrared). The high-resolution airborne imagery datasets were geometrically corrected using post-processing kinematic Global navigation satellite system (horizontal) and the Geoscience Australia 5 m LiDAR-derived Digital Terrain Model (DTM)[2] (vertical) and orthorectified to the DSM generated from the acquired imagery. Bands across the visible (VIS) and near infrared (NIR) were used to detect all living vegetation in sun and shadow. Vegetation not photosynthesizing at the time of acquisition was excluded, including dead wood in tree crowns, deciduous trees without leaves, and dead grass.

A base layer true colour orthomosaic was generated to enable accurate field collection of tree data (Fig. 2a). Vegetation was stratified using the Feature Height Model (FHM = DSM - DTM) into selected height strata (0–3 m, 3–6 m, 6–10 m, 10–15 m, 15–20 m and >20 m) (Fig. 2b), with all vegetation >3 m above the ground classified as 'tree canopy' for further analysis. All datasets were aligned with sub-pixel accuracy and geometrically corrected to an accuracy of +/- 2 × GSD. All multispectral data was radiometrically corrected to reflectance and seamless multispectral orthomosaics generated (e.g., Figs. 2c–2d).

[1] www.arborcarbon.com.au/arbor/remote-sensing-2/index.html
[2] www.ga.gov.au/

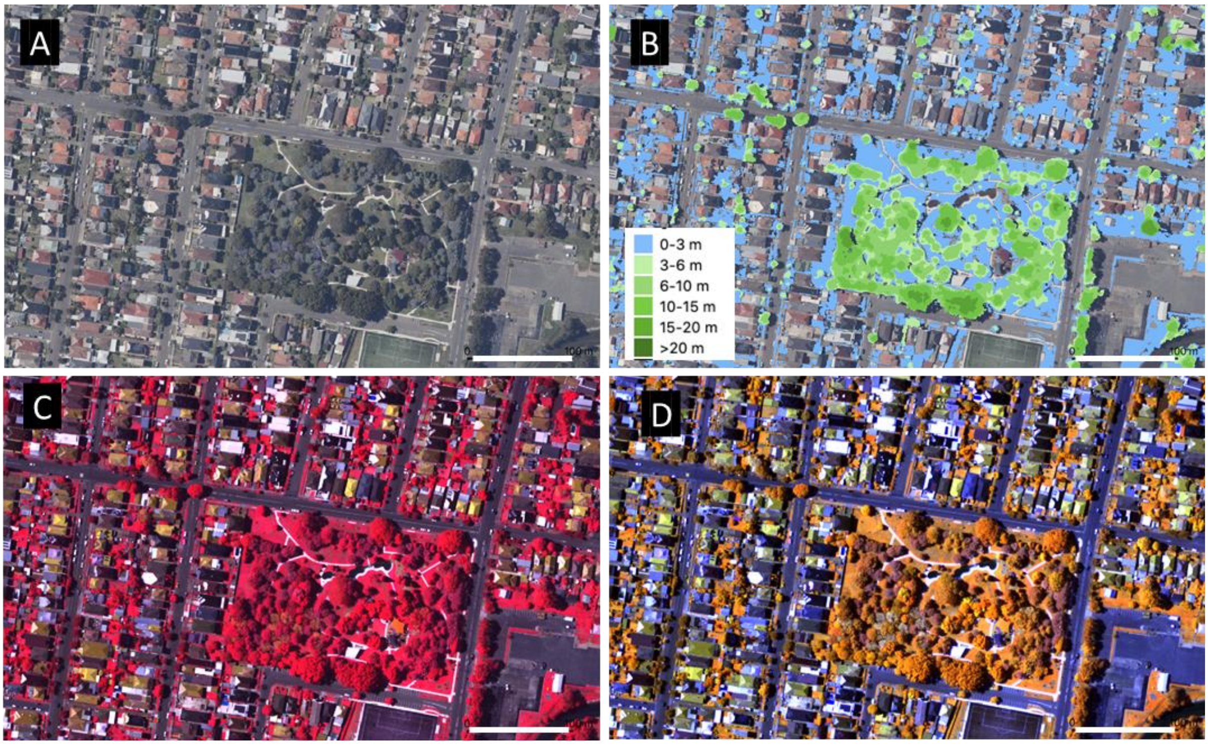

Figure 2. Photogrammetric products from airborne ArborCam™ multispectral imagery over Bayside Council: (A) true colour orthomosaic; (B) height-stratified vegetation overlaid on true colour orthomosaic; (C) false colour composite (near infrared (NIR), red, green); (D) false colour composite (NIR, red-edge, blue). Bar = 100 m.

4.3. Ground truth data

The georeferenced base layer true colour orthomosaic was imported into the Forestry Corporation of NSW MapApp© field mapping program (Version 2.9.9.7, Forestry Corporation of NSW, Sydney, Australia) in an iPad with an in-built GPS. Individual trees of *Pinus* and *Platanus* were then accurately located on the imagery via ground surveys in March 2021 (e.g., Fig. 3c), prior to autumn leaf fall of *Platanus*. Not all trees in Bayside Council were inspected; we primarily focused on areas where we had prior knowledge of the location of stands of *Pinus* and *Platanus* from our forest biosecurity surveillance program. Trees were identified to species, with more than 650 *Pinus* trees mapped onto the imagery (primarily *Pinus radiata*, with smaller numbers of *P. pinaster* Aiton, *P. halepensis* Mill. and *P. ponderosa* P.Lawson & C.Lawson) and 446 *Platanus* trees (primarily *Platanus x acerifolia* (Aiton) Willd., and a few *Pl. orientalis* L.). Trees other than *Pinus* or *Platanus* were not mapped. To be used in the CNN models, each tree point was reviewed and trees of poor crown condition or where the crown could not be easily identified in the imagery were removed from the dataset, leaving a total of 630 *Pinus* and 439 *Platanus*.

4.4. Machine learning CNN models

Data was first pre-processed to create labelled tree polygons to be used in training. Individual tree crowns were detected and delineated across the whole dataset using a CNN model previously developed by ArborCarbon and supported by numerous associated ArborCam multispectral outputs[3]. For the analysis, species-level classifications were ignored, and only genus-level classifications were used. Geolocations of target tree genera (*Pinus* and *Platanus*) identified on the ground were aligned with tree crowns and the tree crowns were classified as *Pinus, Platanus* or 'other' (Fig. 3). As trees other than *Pinus* or *Platanus* were not manually located onto the imagery, for this exercise, we assumed all delineated tree crowns that were not identified in the ground truth dataset were classified as 'other'.

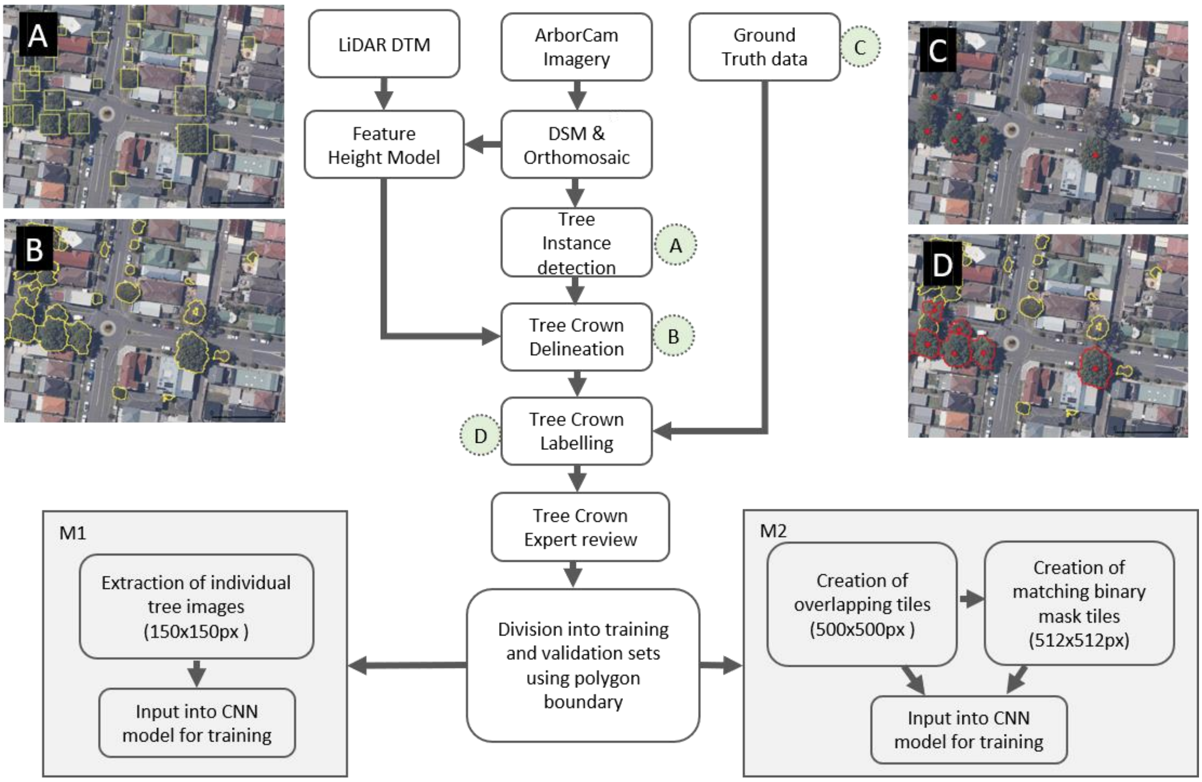

Figure 3. Example of the 'end-to-end' workflow process from data pre-processing to training of the models. Including: (A) tree instance detection, (B) tree crown delineation, (C) addition of ground truth data, (D) eventual tree crown labelling. DTM = digital terrain model; DSM = digital surface model; CNN = convoluted neural network.

In this study, two distinct model frameworks were evaluated (M1 and M2) based on the CNN architecture. M1 used an image classification approach in which the model was trained to predict the genus label (*Platanus, Pinus, other*) when presented with an ArborCam image, cropped around a tree. M2 performed instance segmentation, i.e., distinguished different instances of the same category (e.g., a tree genus). The algorithm detected the targets (i.e., tree crowns), and identified the pixels associated with each instance of the target within the image. M1 and M2 were trained using 525 *Pinus* trees and 388 *Platanus* trees and validated using 105 *Pinus* trees and 41 *Platanus*, respectively. The validation set was defined by manually delineating a contiguous polygon over a subset of the ground truth points. This ensured that the validation set was spatially independent from the training data and there would be no overlap between training and validation trees.

M1 had three target categories: *Platanus, Pinus, Other.* The location of each tree crown was used to clip a 10-band raster image from the ArborCam ortho-mosaic (150 × 150 pixels). These training images were used to train a model to predict the corresponding category (*Platanus, Pinus,* Other). A

[3] www.arborcarbon.com.au/index.html

total of 2,000 ‘other’ trees were selected at random for training and a further 1,014 from within the validation areas were used for validation. A weighted training procedure was used to account for the imbalanced training data. For M2, two separate binary models were trained for each target genus (*Platanus* and *Pinus*). The orthomosaic was clipped into 731 overlapping training tiles (500 × 500 pixels), each containing at least one target tree. A matching mask image was produced for each tile identifying the pixels corresponding to the target trees. All other pixels, including ‘other’ trees, were considered background. The model was then trained to identify which pixels belonged to the target trees. After model training, predictions were output to geospatial vector format, delineating contiguous groups of pixels as a tree.

For each model, training and validation loss was monitored to determine the length of the training period. Training was stopped when validation loss failed to improve on consecutive epochs. A range of standard hyperparameters were evaluated including loss functions, image augmentations, learning rate, batch size etc. however, this was not exhaustive.

4.5. Accuracy assessment

To compare the accuracy of each model, we used common evaluation statistics for classification (Goutte and Gaussier 2005; Powers 2011; Pearse et al. 2021). However, rather than using the model validation metrics produced during training, we first converted our predictions back to a geospatial format for the whole of the validation area. The predicted tree polygons were then compared to the ground truth data by intersection with the training polygons. Predictions which intersected the ground truth tree polygons for the relevant class were considered true positives. Predicted tree canopies that did not intersect a ground-truth canopy polygon of the same class were considered false positives (i.e., a commission error). False negatives were defined as any ground truth tree polygon which did not intersect the predictions (i.e., a tree is missed; an omission error). True negatives were calculated as the total number of trees identified in the validation area subtracting true-positives, false-positives, and false negatives.

We then calculated overall accuracy (a measure of how the classifier’s predictions were correct), precision (i.e., positive predictive value or user’s accuracy; a measure of the proportion of positive predictions that were correct), sensitivity (i.e., recall or producer’s accuracy; a measure of the actual positives that were correctly identified) and the F1-score (the overall accuracy taking both commission and omission errors into account). We also used confusion matrices to illustrate the number of correctly classified trees per genera and the false negatives and false positives.

5. Results

5.1. Classification accuracy

Table 1 shows a comparison between the classification accuracy of M1 and M2. M1 achieved a classification accuracy of 85%, with low precision (41–46%), good sensitivity (90%) for both *Pinus* and *Platanus,* and moderate F1-scores for *Pinus* (56%) and *Platanus* (61%). Classification accuracy for M2 was higher, 92.1% for *Pinus* and 95.2% for *Platanus*, with moderate precision for both *Pinus* (61.3%) and *Platanus* (77.6%) and high sensitivity for both *Pinus* (95.2%) and *Platanus* (92.7%). The F1-score increased around 20 percentage points for the two target genera for M2, up to 74.6% for *Pinus* and 84.4% for *Platanus*.

The confusion matrices (Fig. 4) show the detailed results of predictions for the two models and whether they were accurate (true negative, true positive) or incorrect (false negative, false positive).

The number in each cell represents the number of classified images (trees). For M1, a high number of 'other' trees were classified as *Pinus* and *Platanus* (i.e., false positives), 108 and 53, respectively, while a relatively low number of *Pinus* and *Platanus* trees were misclassified as 'other' (i.e., false negatives), 11 and 4, respectively. For M2, although a relatively high number of false positives were predicted (63 for *Pinus* and 11 for *Platanus*), the false negatives were low (5 for *Pinus* and 3 for *Platanus*).

Table 1. Classification accuracy metrics for the three models M1 and M2-Pinus and M2-Platanus.

Model	**M1**			**M2-Pinus**	**M2-Platanus**
Target	*Pinus*	*Platanus*	Other	*Pinus*	*Platanus*
Accuracy	0.85*			0.921	0.952
Precision	0.47	0.41	0.98	0.613	0.776
Sensitivity	0.90	0.90	0.84	0.952	0.927
F1-score	0.56	0.61	0.91	0.746	0.844

* accuracy for three classes

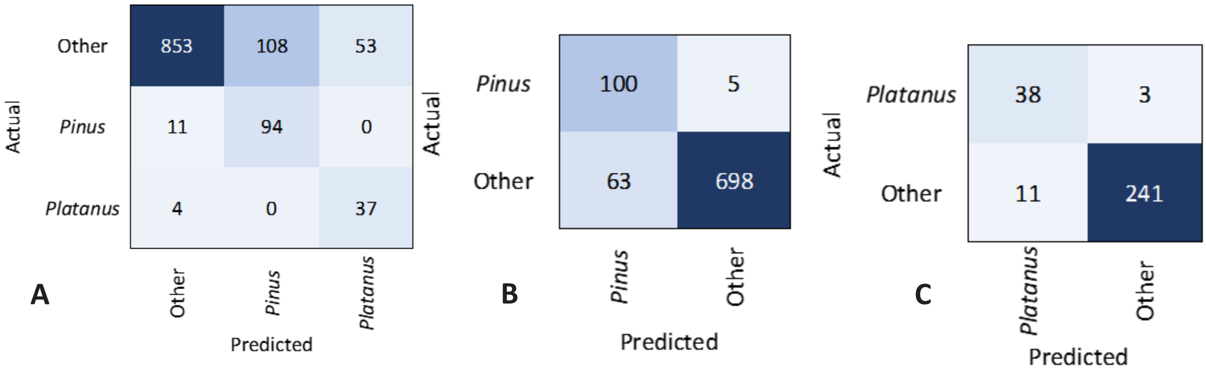

Figure 4. Confusion matrices of convolutional neural networks for (A) M1, (B) M2 for *Pinus* and (C) M2 for *Platanus*. The vertical axis is the ground truth and the horizontal axis the model prediction. The number in each cell indicates the number of classified images (=trees).

6. Discussion and Conclusion

This study demonstrated the effectiveness of using CNN deep learning algorithms with high-spatial resolution ArborCam imagery to accurately classify *Pinus* and *Platanus* trees in a heterogenous urban landscape. Numerous automated machine learning methods have been applied to the detection of individual tree crowns using high spatial resolution imagery in urban and peri-urban areas for a range of outputs, including green-space and tree species mapping, inventory and assessment, change detection, ecosystem services, and biomass and carbon estimation (Fassnacht et al. 2016; Shahtahmassebi et al. 2021). Recently, deep learning has emerged as a powerful tool due to its superior performance in terms of the accuracy and versatility of the models. There has been a sharp increase in the application of CNNs which work on raw data and are automatically able to detect and label specific objects especially for tree species mapping (Kattenborn et al. 2021). However, the use of such an approach to aid in biosecurity is only just now being investigated. Pearse et al. (2021) evaluated a deep learning CNN model with high-resolution aerial imagery to detect and map *Metrosideros excelsa* Sol. ex Gaertn. trees in urban areas in New Zealand during the attempted eradication of *Austropuccinia psidii* (G.Winter) Beenken. They demonstrated the application of this cost-effective approach for use in surveillance over large areas following the detection of an invasive species. Our work expands on this by targeting two key host genera in areas of high risk for establishment of exotic forest pests in Australia to aid in biosecurity surveillance, prior to an incursion (i.e., sentinel tree surveillance) and in the event of an incursion (e.g., delimiting surveillance).

Using high-resolution airborne multispectral aerial imagery and a CNN framework, we were able to delineate and classify with high accuracy individual trees to genus level in a heterogenous, complex urban landscape. M1 achieved a classification accuracy of 85%, which improved to 92.1% (*Pinus*) and 95.2% (*Platanus*) with M2. This is comparable to similar studies using RGB imagery, with Pearse et al. (2021) achieving an accuracy of 92.7% to 97.4% for a single species in New Zealand, using 10 cm resolution imagery. These higher accuracy results were obtained using multi-temporal datasets and incorporating clear phenological traits (i.e., flowering) in model development (Pearse et al. 2021). Martins et al. (2021) reported accuracy (producer's accuracy) between 85.5% and 89.9% for multiple species in Brazil using 15 cm resolution. Although in this study (Martins et al. 2021), the metric reported was the accuracy of pixel-wise classification (i.e., the number of pixels within each image classified as belonging to the targets). This differs from our study because of the differing objectives. Our study was focused on the biosecurity application, where the presence/absence of the target is the only metric of interest, rather than the precision of the tree crown delineation.

Lower classification accuracies have been achieved using low spatial resolution satellite imagery (e.g., 84.2% [Jombo et al. 2020] to 85.5% [Tiggs et al. 2013]). Li et al. (2015) increased classification accuracy by 10–20% by conducting bi-temporal analysis of satellite imagery (summer and autumn), with 80.3% overall accuracy at one site and 92.5% overall accuracy at a second site. Numerous studies have shown the potential for individual tree species detection and classification using CNNs of multispectral imagery captured by UAVs, with accuracies generally greater than 90% (Csillik et al. 2018; Egli and Höpke 2020; Lobo Torres et al. 2021; Onishi and Ike 2021). UAVs, however, while able to capture high spatial resolution at low-cost, are typically limited in spatial extent and locations where they can be flown. Multispectral imagery from fixed-wing aircraft is a good middle ground, with high spatial resolution, large spatial extent, and relatively inexpensive (Fassnacht et al. 2016; Shahtahmassebi et al. 2021). There is now a growth in studies using CNNs with multispectral imagery from fixed-wing aircraft to detect and map tree species with high accuracy (Martins et al. 2021; Pearse et al. 2021; Kattenborn et al. 2020).

A key reason for the success of the current study was the accurate ground validation of tree species directly onto the high-resolution imagery. We mapped 1069 individual tree crowns to the exact location on the ArborCam imagery and achieved greater than 92% accuracy. Martins et al. (2021) geolocated substantially less trees — 370 across nine tree species — but still obtained high species classification accuracy (>85%) in an urban landscape in Brazil, with accuracy increasing to 89.8% when they used data for species with more than 30 individuals represented. Pearse et al. (2021) geolocated 2,300 trees, including target and non-target ('other') species, and obtained accuracies of 92.7%, which increased to 97.4% when they included phenology in the classification model.

The accuracies in our study are likely to be acceptable for early-detection surveillance as part of a high-risk site surveillance program. However, if we are to use this technology to identify and map host species in an emergency response, an exhaustive detection of hosts is needed. In this case, along with overall accuracy we also need to understand both precision and sensitivity (Goutte and

Gaussier 2005; Powers 2011; Pearse et al. 2021). Our study demonstrated relatively low levels of false positives are detected, and while these may result in occasional unnecessary surveillance costs being incurred, these are likely to be small compared to the efficiencies gained from not having to undertake ground surveys. There are also added benefits of being able to identify trees across a greater area in both public and private land. Sensitivity in a biosecurity surveillance context means that target hosts are not detected by the classifier (i.e., false negatives), and potentially not assessed for pest attack nor selected for subsequent control, resulting in an undetected source of ongoing infestation. M2 in our study increased precision from 41.0% (*Platanus*) and 46.5% (*Pinus*) to 77.6% (*Platanus*) and 61.3% (*Pinus*), which still resulted in 74 trees incorrectly identified (false positives). Sensitivity for both models was good, with M2 increasing sensitivity from 90.2% (*Platanus*) and 89.5% (*Pinus*) to 92.7% (*Platanus*) and 95.2% (*Pinus*). This resulted in only 8 trees not being detected (false negatives). In the context of delimiting surveillance during an emergency response, sensitivity is the most important metric, as there is a potentially high consequence of a false negative (Powers 2011). However, it is important to evaluate these accuracies against the alternative approach, which currently involves manual on-ground assessments, wherein many potential trees go undetected.

Current host mapping via ground surveys is labour- and resource-intensive, unable to cover large areas quickly, and provides incomplete coverage (i.e., a significant proportion of trees remain undetected). To effectively map the majority of host trees in a given local government area, personnel need to travel hundreds of kilometres of road in vehicles and by foot, traversing a mix of public and private property. For example, there are more than 530 km of roads in Bayside Council and over 500 ha of parks. Manual identification of trees by trained personnel could be assumed to have an accuracy of near 100%. However, this does not account for the numerous challenges such as access to private land for inspection, the limited area which can be accurately covered within a period of time and finding adequate numbers of trained staff to rapidly respond to emergency incursions. The remote sensing approach has the advantage that the accuracy level can be easily evaluated and understood and can be incorporated into the risk assessment process. Furthermore, detection of target trees on private property enables targeted contact with private landowners. Also, the cost at which a given area can be assessed, and speed, is likely to be much lower using remote sensing compared with manual identification alone. Given that the speed of a biosecurity response can greatly increase its chances of success and reduce subsequent management costs, the advantage of a rapid turnaround should not be undervalued.

Limitations of this study primarily focus on the fact 'other' trees were not validated on the ground. Also, while an extensive survey was conducted to map *Pinus* and *Platanus*, not all roads were traversed and many trees on private property would not have been visible, and so it is likely that not all *Pinus* and *Platanus* trees were mapped (a known limitation of ground validation); any missed *Pinus* or *Platanus* would have been allocated as an 'other' tree in our study. To test this, we used Google Street View™ to validate several of the false positive results (i.e., the model identified a target tree [*Pinus* or *Platanus*], but we had not mapped it as a target tree on the ground). In the few cases we investigated (data not shown), the model prediction was correct (i.e., the predicted *Platanus* tree was in fact a *Platanus*); we had just not surveyed the roads where those trees were located. Others have used Google Street View for tree classification and urban green-space mapping (Li et al. 2015; Richards and Edwards 2017; Barbierato et al. 2020). We suggest combing aerial imagery with Google Street View and classical ground validation to detect and classify host trees for biosecurity surveillance more accurately and efficiently.

The potential benefits of conducting early-detection surveillance in urban areas is evidenced by many invasive species being detected on amenity trees in urban areas. Well known examples include *Anoplophora glabripennis* (Dodds and Orwig 2011), *Agrilus planipennis* (Siegert et al. 2014), *Phytophthora ramorum* (Brasier et al. 2004), *Hymenoscyphus fraxineus* (Mitchell et al. 2014), *Ophiostoma novo-ulmi* (Ganely and Bulman 2016) and *Ceratocystis platani* (Engelbrecht et al. 2014). In Australia, Carnegie and Nahrung (2019) identified numerous examples of new detections of exotic pests detected on amenity trees in urban settings in the past 25 years, including *Marchelina hellenica* (Gennadius) (Plant Health Australia 2017) and *Bursaphelenchus hunanensis* Yin, Fang & Tarjan (Hodda et al. 2004; Smith et al. 2008) in Melbourne, *Rugonectria castaneicola* (W. Yamam. & Oyasu) Hirooka & P. Chaverri (Carnegie and Nahrung 2019) and *Corythucha ciliata* (Say) in Sydney (Dominak et al. 2007), *Essigella californica* (Essig.) in Canberra (Carver and Kent 2000) and *Trichoferus campestris* (Faldermann) in Brisbane (Plant Health Australia 2017). More recent examples include *Pseudocercospora platanigena* Videira & Crous in Sydney (Carnegie et al. 2021) and *Euwallacea fornicatus* in Perth (Department of Primary Industries and Regional Development 2022). If exotic pests are not detected early enough, they can establish and spread, making eradication or containment attempts more costly and challenging (Liebhold et al. 2016; Lovett et al. 2016), and the reason why so few exotic forest pest incursions have been eradicated (Anderson et al. 2017; Liebhold and Kean 2019; Carnegie and Nahrung 2019). Current early-detection surveillance for forest pests in Australia is inadequate (Tovar et al. 2017; Carnegie et al. 2018; Carnegie et al. 2022). Annual post-border surveillance in areas at high risk for entry of exotic forest pests is not conducted nationally or in a coordinated fashion. It is often limited by a lack of adequate human and material resources and ad hoc knowledge of the potential host trees existing within risk areas. This in turn limits the ability to monitor or survey for exotic pest through inspection of potential host for the purposes of early detection or during an emergency incursion response. A proposed national program that includes specific surveillance through high-risk site surveillance and general surveillance through stakeholder engagement and training will greatly enhance early detection (Carnegie et al. 2022). Knowing the distribution of hosts of primary pests is key to such surveillance.

There is wide variation in cost, spatial extent captured, and species classification accuracy between the various remote sensing platforms (Fassnacht et al. 2016; Shahtahmassebi et al. 2021). Hyperspectral plus LiDAR is high accuracy and high cost, but generally lower resolution and spatial coverage. High-resolution multispectral is generally good for accuracy, moderate cost, and higher spatial resolution and extent. Satellites are very low cost to free, large spatial extent, but lower spatial resolution and accuracy. The high accuracy in our study of the two target tree genera using high-resolution aerial imagery shows promise for this method to be used more broadly. The scope for using remote sensing and machine learning for forest biosecurity surveillance in urban landscapes is enormous. We propose a technology-driven host-mapping biosecurity partnership whereby state and national biosecurity agencies work with local councils and commercial entities to map key hosts of biosecurity concern. Many local councils already capture imagery for management of urban green space (e.g., City of Melbourne 2011; City of Sydney 2013; City of South Perth 2017). Our proposed partnership would utilise this imagery, collaboratively, for multiple beneficial outcomes. Pre-existing or newly captured imagery, of adequate spatial and spectral resolution and overlap, could be used to develop models and produce maps of many other key hosts. This would require some ground-truthing for model validation, which could be captured by local council staff.

Further work is needed to refine the model. Testing of the model in other local council areas is needed. Optimising the amount of ground-truthing is required to balance the fine-line between model accuracy (with lots of ground-truthing) and limited resources (less ground-truthing). Furthermore, we need to determine thresholds of accuracy for the two types of surveillance needs. Early detection surveillance (high-risk site surveillance) requires that many hosts are located across a particular area, but not all of them, whereases during an emergency response (eradication) a higher accuracy threshold may be needed. It might be that most hosts are located using remote sensing and machine learning technology then the remaining located by traditional methods. This is likely to be more efficient at tree-location than traditional ground surveys only. Factoring in the cost of airborne acquisition and data analysis needs to be considered, but in instances where the area of interest is large, these costs, both in time and human resources, may be less than large scale ground surveillance. Our study was a proof-of-concept; this method has recently been used to map host trees of *Euwallacea fornicatus* in Perth following the detection of this invasive polyphagous pest in August 2021 (P. Barber, pers. comm.). A review of that program will shed light on the feasibility of this technology for future programs.

Conclusion

This study evaluated high-resolution airborne ArborCam imagery for tree species classification in a complex urban environment as a potential application for forest biosecurity surveillance. An object instance segmentation of tree crowns was achieved using a deep learning CNN algorithm; one model for all trees; a second model running on *Pinus* and *Platanus*. Two dominant tree genera, *Pinus* and *Platanus*, were examined in a single local government area in Sydney, Australia. These two genera are hosts of high priority tree pests for Australia.

Overall accuracy of M1 was 85%, which increased to 92.1% for *Pinus* and 95.2% for *Platanus* with M2. While precision was relatively low (41.0%–46.5% for M1; 61.3%–77.6% for M2), sensitivity was high for both the first (89.5%–90.2%) and second (92.7%–95.2%) model. We suggest that sensitivity is the most important accuracy metric for biosecurity surveillance. While these accuracies may satisfy requirements for the location of sentinel trees for early-detection surveillance, they may not satisfy requirements for emergency response surveillance following the detection of an invasive pest. More work may be needed to improve these accuracies.

Our future work will focus on capturing ground data for the 'other' tree category and investigating the false positives and false negatives in the current data. This work then needs to be expanded to a broader suite of tree species and across a wider geographic area. There is also scope to investigate differences in accuracy between RBG and multispectral imagery, or using bi-temporal imagery. If our study proves applicable across a broader range of urban landscapes and city councils it will not only be a game-changer for forest biosecurity in Australia but also for urban green space management more broadly.

7. Recommendations

We recommend a technology-driven host-mapping biosecurity partnership whereby state and national biosecurity agencies work with local councils and commercial entities to map key hosts of biosecurity concern.

9. Appendices, References, Publications etc.

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Author statement

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Publications

Carnegie AJ, Eslick, H, Barber P, Nagel M, Stone C (2022). Airborne multispectral imagery and deep learning for biosecurity surveillance of invasive forest pests in urban landscapes. Urban Forestry & Urban Greening submitted

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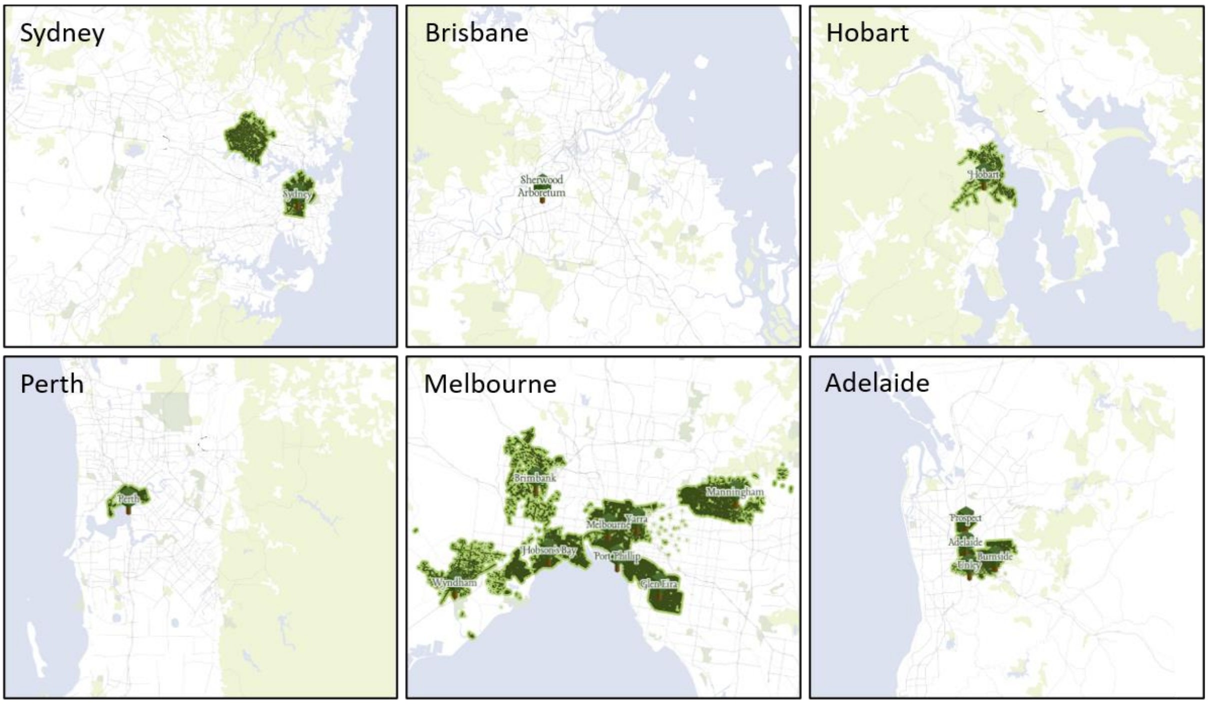
Supplementary Figure 1. Publicly available street-tree data for State capitals in Australia; available from the Open Trees Database [http://opentrees.org/#pos=1/-37.8/145]. [Accessed 14/02/2022]



Supplementary Table 1. Invasive species identified as priority pests by the Australian government and plant industries whose hosts include *Pinus* or *Platanus*. NPPP = National Priority Plant Pest; EEPL = Exotic Environmental Pest List. HRSS = High Risk Site Surveillance.

Pest/Pathogen	**Common name**	**Host targeted during HRSS**	**Species on National or Industry High Priority Pest list** #	**Other industries potentially affected** *
Anoplophora glabripennis Anoplophora chinensis Anoplophora malasiaca	Asian longhorn beetle, Black and white citrus longhorn, White-spotted longhorn beetle	*Platanus*	NPPP	Citrus, Apples & Pears, Walnut, Stonefruit, Chestnuts, Blueberries, Lychees, amenity, environment
Arhopalus ferus	Burnt pine longhorn beetle	*Pinus*		Plantation Forests, amenity
Dendroctonus ponderosae^	Mountain pine beetle	*Pinus*	Plantation Forests	amenity
Dendroctonus valens	Red turpentine beetle	*Pinus*	Plantation Forests	amenity
Endocronartium harknessii^	Western gall rust	*Pinus*	Plantation Forests	amenity
Euwallacea fornicatus[1]	Polyphagous shot hole borer	*Platanus*	EEPL	Amenity, nursery, fruit, nut tree, plantation forestry[¥]
Fusarium euwallacea[1]	Fusarium dieback	*Platanus*	EEPL	Amenity, nursery, fruit, nut tree, plantation forestry[¥]
Fusarium circinatum^	Pine pitch canker	*Pinus*	NPPP, Plantation Forests	amenity
Hylesia nigricans	Burning moth	*Platanus*	Plantation Forests	Almonds, Apples & Pears, Stonefruit, Cherries, Chestnuts,
Ips typographus^	Spruce bark beetle	*Pinus*	Plantation Forests	amenity
Lymantria dispar complex^	Gypsy moths	*Pinus, Platanus*	NPPP, Apples & Pears, Chestnuts, Hazelnuts, Pistachios, Plantation Forests, Production Nurseries, Stonefruit, Walnuts	amenity, environment

Supplementary Table 1 continued

Pest/Pathogen	Common name	Host targeted for HRSS	Species on National or Industry High Priority Pest list #	Other industries potentially affected *
Lymantria monacha^	Nun moth	*Pinus, Platanus*	Apples & Pears, Plantation Forests, Truffles,	Blueberries, Stonefruit, amenity
Marchalina hellenica^^	Giant pine scale	*Pinus*		Plantation Forests, amenity
Monochamus alternatus[2]^ *Monochamus galloprovincialis*[2]	Pine sawyer beetles	*Pinus*	NPPP, Plantation Forests	amenity
Bursaphelenchus xylophilus[2]^	Pine wilt nematode	*Pinus*	NPPP, Plantation Forests	amenity
Orgyia thyellina^	White spotted tussock moth	*Pinus*	Plantation Forests	amenity
Phytophthora pinifolia	Dano foliar del Pino	*Pinus*	Plantation Forests	amenity
Phytophthora ramorum^	Sudden oak death, ramorum blight	*Pinus, Platanus*	NPPP, EEPL, Avocado, Blueberries, Chestnuts, Hazelnuts, Macadamias, Plantation Forests, Production Nurseries, Tea Tree, Truffles	Amenity
Phytophthra pluvialis	Red needle cast	*Pinus*	Plantation Forests	amenity
Tomicus piniperda	Pine shoot beetle	*Pinus*	Plantation Forests	amenity
Urocerus gigas^	Giant wood wasp	*Pinus*	Plantation Forests	amenity

www.planthealthaustralia.com.au/national-programs/national-plant-biosecurity-status-report/

* www.agriculture.gov.au/pests-diseases-weeds/plant; www.dpi.gov.au/biosecurity/plant/insect-pests-and-plant-diseases/; www.planthealthaustralia.com.au/industries/plantation-forestry/

[1, 2] Insect–pathogen/nematode vector

^ Notifiable pest in New South Wales [https://legislation.nsw.gov.au/view/html/inforce/current/act-2015-024#sch.2]

^^ Exotic to New South Wales

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