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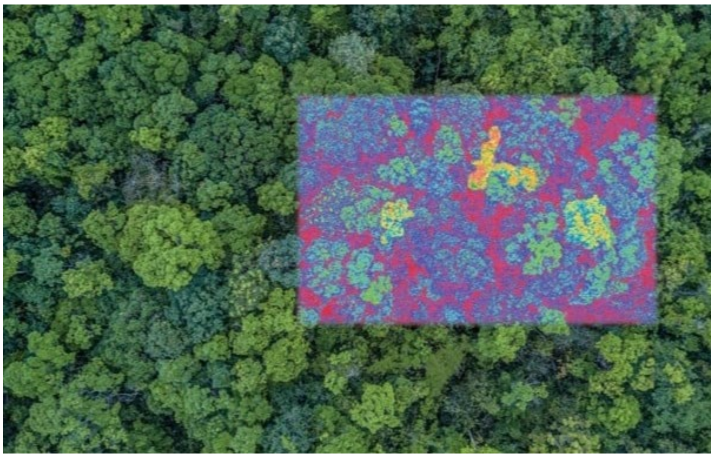
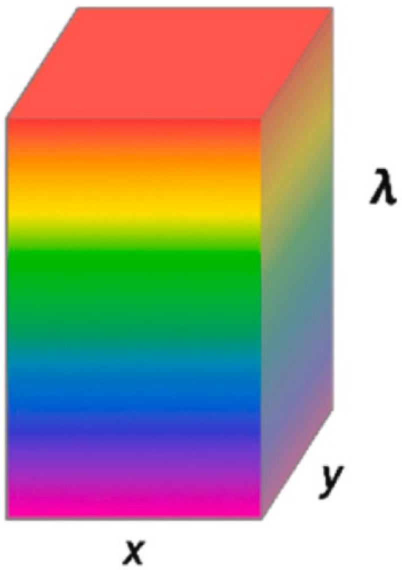
Christine Stone, NSW DPIRD Forest Science
February 2026





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Application of hyperspectral imagery for the identification and mapping of eucalypt species - A Review

Christine Stone, NSW DPIRD Forestry Research, February 2026

Purpose of this Review

The expanding deficit in the supply of timber grown in NSW is acknowledged by industry, government and community, resulting in the general acceptance of the need for a program to expand the plantation estate. While the main focus of this expansion will be on softwoods, the decline in output from native forests necessitates expansion of the hardwood timber plantation estate also. Subject to available funding, a project consisting of 3 phases has been proposed. The first phase includes a stock-take of current hardwood plantations in NSW, that is, quantifying the status of existing plantations in terms of extent, species composition and condition. Most hardwood plantations in NSW, an area that covers an estimated 96,000 ha, are known to occur principally in the coastal Bioregions. Accurate spatial assessment of regional areas at a landscape scale can only be achieved cost and time-effectively through the use of remote sensing. One of the specific aims of the proposed project is to assess existing plantations in terms of species, stocking, age-class and height to enable assessments of timber volume and carbon. The remote identification of eucalypt species will be challenging but advances in the acquisition and analysis of remotely sensed imagery, in particular, hyperspectral imagery, makes this task worthy of investigation. This review provides an introduction into the potential application of hyperspectral imagery for identifying the species composition of existing eucalypt plantations in NSW.

Introduction to Hyperspectral Imaging (HSI)

Hyperspectral imaging (HSI) captures detailed spectral information across hundreds of narrow wavelength bands, creating a three dimensional (3D) 'hypercube' (two spatial dimensions and one spectral) for each pixel. That is, HSI simultaneously captures spatial and dense spectral information, recording the electromagnetic energy from the visible, near infrared and short wavelength regions (from 380 – 2500 nm). Unlike multispectral sensors which use a few, separate, broad bands providing non-continuous information related to a target object's reflectance or absorption characteristics, hyperspectral sensors have hundreds of narrow, contiguous spectral bands (100+), creating detailed spectral profiles.

The general biophysical and biochemical features of vegetation result in a common, generic spectral signature across the range of wavebands (Figure 1). Healthy plant foliage reflects strongly in the green and near-infrared (NIR) ranges, while stress (e.g. from drought or disease) alters these signatures through changes in leaf pigments, leaf cell structure and water content. In addition, HSI can capture the subtle differences in these leaf properties that exist between tree species (Figure 2). Although more challenging, HSI acquired above tree crowns can also be used to detect differences in shape, structure and texture of individual tree crowns, features which can contribute to tree species identification.

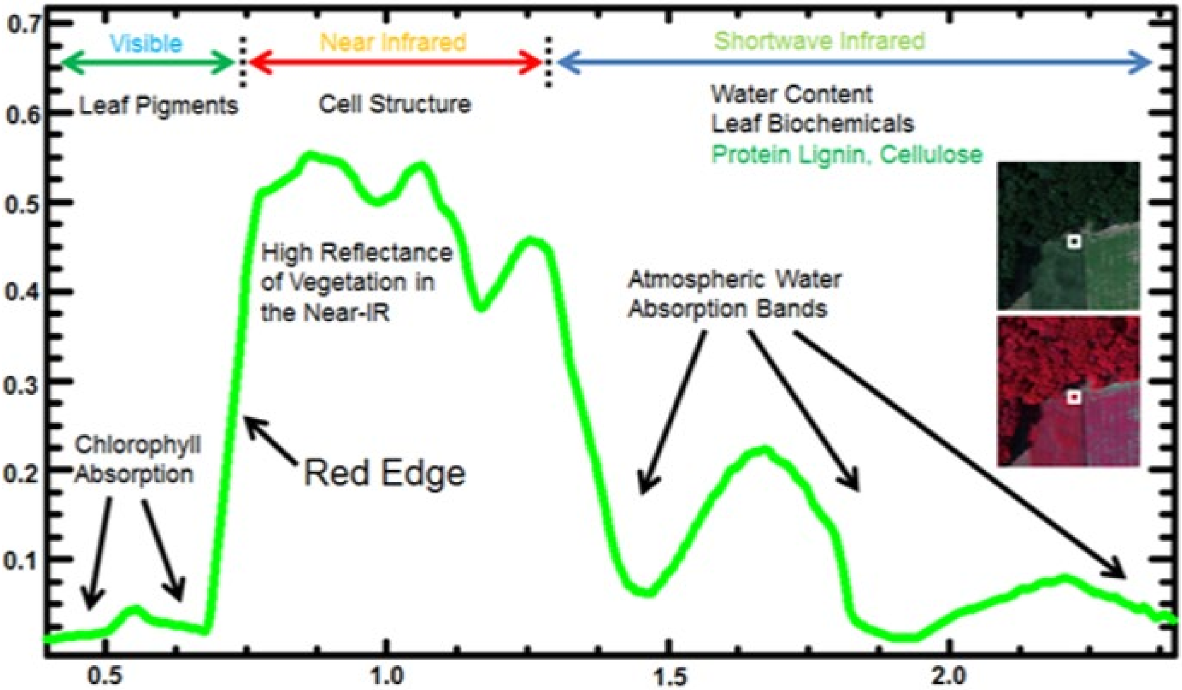

Figure 1. Typical hyperspectral spectral profile (=signature) for vegetation identifying wavebands (image retreived from NV5 Geospatial (ENVI) software website)

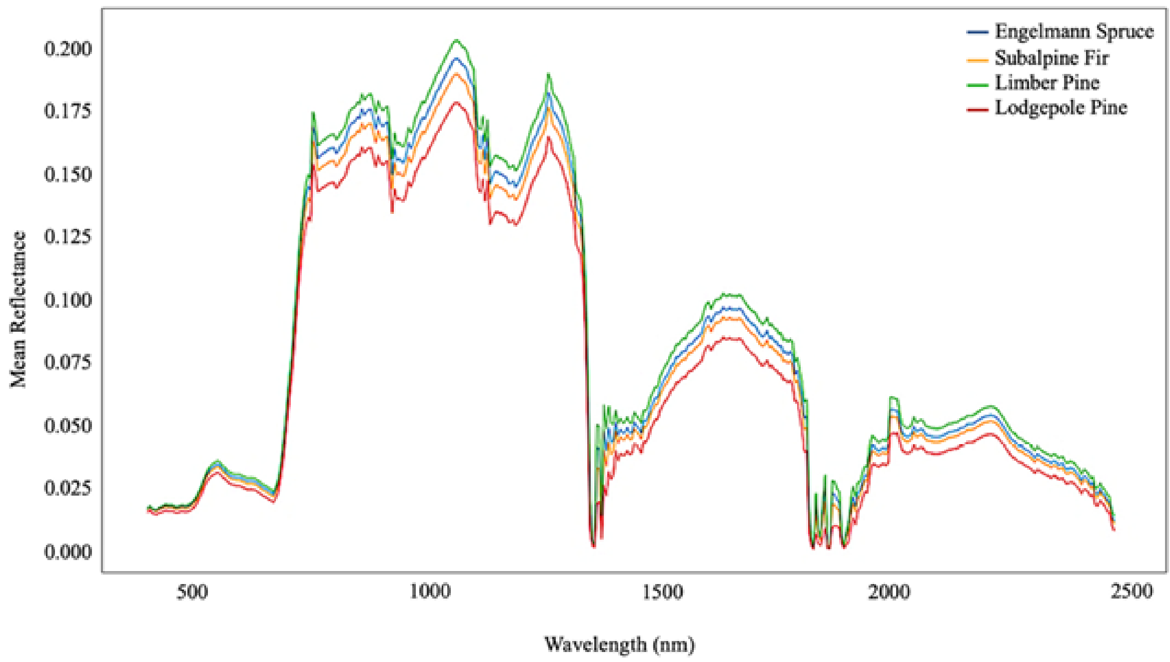

Figure 2. Comparison of mean hyperspectral reflectance extracted from crown polygons of four tree species obtained from airborne HSI (Ni-Meister *et al*. 2024, Figure 8.)

While it is possible to detect statistical differences in the spectral signatures of leaves from various *Eucalyptus* species (Kumar 2007), it is much more difficult to discriminate *Eucalyptus* species from above. Eucalypt species often exhibit relatively large intra-class variability of canopy properties, related to differences in tree age, (e.g. presence of juvenile and/or adult foliage), seasonal responses in leaf phenology (e.g. ratio of immature leaves versus fully expanded mature leaves) and tree health. In addition, tree structural characteristics, such as pendulous leaves and often open crowns, and differences in tree density make it notoriously difficult to discriminate eucalypt species using remote sensing data (Youngentob *et al*. 2011). There are also several more generic challenges associated with tree species classification, such as spectral mixing within tree canopies and lack of spatially precise ground data for training model classifiers.

In addition, while the narrow bands provide more biophysical and biochemical details of vegetation than the wider bands of multispectral imagery, hyperspectral imagery is more expensive and complex to acquire and analyse. Furthermore, the information rich HSI datasets suffer from high spectral correlation and information redundancy. Therefore, there exists analytical trade-offs between the need to reduce the dimensionality of HSI data and fully utilising the spectral and spatial information it provides. Considering the often-limited areas covered by HSI and the cost of collecting ground samples in forests, operationally it is often also challenging to acquire sufficient reference data required by modern classification algorithms (e.g. Tong & Zhang 2024). Furthermore, the large 3D datasets associated HSI also require powerful computing and data storage capacity.

Below is a more detailed discussion on the potential of HSI for tree species classification (Figure 3) and in particular, eucalypt species, as well as the associated challenges and potential solutions presented in the scientific literature.

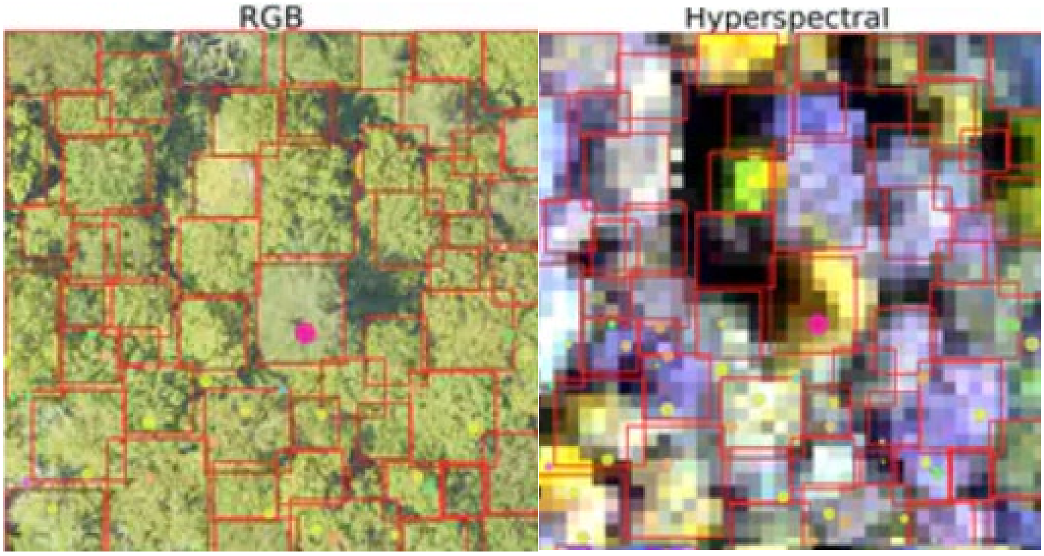

Figure 3. Comparison of individual tree crowns in airborne RGB imagery and classified HSI. (Weinstein *et al*. 2021)

Hyperspectral systems

In recent years, there have been significant advances in HSI sensor systems including the availability of remote platforms with enhanced hardware and software sophistication and miniaturisation (Bhargava *et al.* 2024). Hyperspectral sensors can capture data in the following format categories: point scanning (whiskbroom), line scanning (push broom) or snapshot scanning. These sensors are now deployed on a range of remote platforms including hand-held, UAV, plane and satellite platforms offering a myriad of spatial resolutions and spectral ranges covered by the wavebands. Below is a summary list of HSI systems and associated imagery available in Australia.

Satellite hyperspectral sensors

Hyperspectral satellite imagery is accessible in Australia through partnerships between local providers (e.g. Geoimage and Geopera) and global data companies (e.g. Pixxel and Wyvern). The Australian companies can also provide hyperspectral data processing and analysis.

● Pixxel's Firefly Hyperspectral Constellation – launched in 2025, this is currently the world's highest spatial resolution (5m) hyperspectral satellite system. It can capture 161 spectral bands and has a revisit time of up to every four days.

● Wyvern's Dragonette Hyperspectral constellation – captures 23 to 31 spectral bands across the 503-799 nm wavelength with a nadir spatial resolution of 5.3m and a 20 km swath width.

● The German hyperspectral satellite EnMAP has 240 spectral bands (from 420-2450 nm), a spatial resolution of 30m and a revisit time of 4 days.

● Planet Labs in partnership with NASA's JPL in 2024 launched a hyperspectral satellite constellation (Tanager mission, 400 – 2500 nm 30 m spatial resolution), designed principally to detect and monitor methane and CO_2 point source emissions but which is also being used to detect wildfires and droughts.

● The HyperScout 2 hyperspectral sensor on the South Australian Kanyini satellite was commissioned in early 2025. The hyperspectral sensor has 50 bands in the VNIR (400-1000nm) with a Ground Sampling Distance (GSD) of 5 m. It has significant potential for forest health monitoring and may be suitable for tree species identification in plantations. Imagery may be tasked through the SmartSat CRC or the South Australian Space Industry Centre.

Airborne Hyperspectral Systems

● The HyVista Corporation based in Norwest, Sydney, routinely captures HyMap (Intspec Systems) hyperspectral data for environmental monitoring. The HyMap provides 128 wavebands from 450 nm – to 2500 nm and a ground spatial resolution of 2 – 10 m. The company recently collaborated in a research project aimed at identifying eucalypt tree species to predict koala habitat (Orlando *et al*. 2025). They achieved a high classification accuracy applying a Multilayer Perception model (a Deep Learning algorithm) trained on a 'pixel-based' dataset.

● The Australian ArboCarbon company has airborne hyperspectral capability. In addition, they have developed their 'ArborCam' which has 11 narrow and broad wavebands selected specifically for monitoring trees.

● Airborne Research Australia (ARA) is based at the Parafield airfield, Adelaide. ARA has an aircraft fitted with two SPECIM Asia EAGLE 'push broom' scanners, as well as a Riegl Q560 Lidar scanner. The HSI has a spatial resolution of 0.5 m. The ARA is a research institute engaged in environmental research from aircraft and has acquired HSI data over the TERN supersites.

● The Hyperspectral and Thermal Remote Sensing Laboratory, University of Melbourne. This facility is led by the vegetation remote sensing expert, Prof. Pablo Zarco-Tejada who leads research into the detection and mapping of vegetation stress.

● The University of NSW have recently acquired an airborne hyperspectral sensor (contact Peter Mumford, UNSW School of Aviation's Airborne Scientific Officer). The associated research team is developing deep learning (DL) methods for hyperspectral image classification. Their DL models overcome data scarcity, improve classification accuracy for small training sets and extract meaningful information from rich hyperspectral datasets.

● The NASA sponsored AVIRIS-NG airborne spectrometer has a narrow band spectral range from 380-2510 nm and spatial resolution as small as 4 m. HSI datasets from this system are commonly accessed by North American researchers.

UAV platforms

Many Australian universities have UAV/hyperspectral systems as well as the Australian company Australian UAV Service. Available UAV hyperspectral sensors include push-broom, whiskbroom and snapshot spectral scanning. Many of these cameras are integrated with UAV navigation units for precise mapping.

In addition, there are now UAV systems with > 4 multispectral bands, e.g. the MicaSense Dual Camera System which consists of two five-band multispectral cameras with 10 bands covering the visible and near-infrared spectra.

Multispectral satellites

Most studies evaluating HSI data for classifying eucalypt species have focused on data acquired by UAV or airborne platforms. Far fewer have evaluated satellite platforms, partially due to their lower spatial and spectral resolution. This situation is rapidly changing with the continuous improvement of satellite resolution specifications. Peerbhay *et al*. (2014), for example, successfully applied partial least squares discriminant analysis to WorldView-2 imagery (8 bands, 2 m spatial resolution) to map six tree species in South African plantations, including *E. grandis*, *E. nitens*, and *E. smithii*. Pinheiro-Ferreira *et al*. (2019) used the higher spatial resolution of WorldView-3 with a panchromatic band at 0.3 m spatial resolution, to identify individual tree crowns in a tropical forest and then applied spectral and textural analysis as well as sub-pixel fractions of Non-Photosynthetic Vegetation, Green Vegetation and Shade for species classification using a Support Vector Machine(SVM) classifier on the extracted crown data. In an object-based approach, Usman *et al.* (2023) applied Machine Learning (ML) models using WorldView-2 imagery to map tree species after segmenting tree crowns using the object-based software GEOBIA.

The fusion of satellite multispectral imagery with datasets that can be used to segment individual tree crowns can also facilitate tree species classification. Alonso *et al*. (2024), for example, evaluated combinations of metrics obtained from *temporal* Sentinel-2 and Worldview-3 (1.2 m multispectral and 0.3 m panchromatic bands) and Airborne Laser Scanning (ALS) data to map stands of *E. globulus* and *E. nitens*. Supervised classifications were performed using a modified Convolutional Neural Network (CNN) architecture. They reported, however, that Worldview-3 images alone have a low potential to differentiate between the two species. The highest accuracies were obtained when using Sentinel-2 data in combination with Lidar point clouds and when using Sentinnel-2 data in a multitemporal approach.

HSI acquisition and calibration

Prior to the application of HSI classification techniques, it is necessary to perform pre-processing on the acquired images. This involves a sequence of corrections designed to transform raw digital signals into geolocated reflectance data. It is well known that in HSI certain hyperspectral bands exhibit higher levels of noise compared to others, notably bands that are highly absorbed by water molecules (Figure1). Sensor noise for some bands may also exist. In the pre-processing phase, these bands can be removed through a simple de-noising operation (Ni-Meister *et al*. 2024). Challenges associated with the acquisition of HSI also include issues common to all remote systems acquiring optical imagery, including atmospheric effects such as variable illumination that can decrease the signal-to-noise ratio, and the requirement for image radiometric calibration, atmospheric correction and georeferencing. A common approach for the geometric calibration of UAV and airborne HSI is the use of Ground Control Points (GCPs) and for radiometric correction, the ground placement of calibration panels (e.g. Yao *et al.* 2023). Orthorectification can be achieved using a lidar Digital Elevation Model (DEM).

There now are several hyperspectral image software packages, with one of the most popular being ENVI (NV5 Geospatial). This comprehensive, commercial software package provides routines for the processing and analysis of HSI. CSIRO (Data 61) has also developed a package called Scyllarus hyperspectral imaging software, while there are specialized Python libraries such as Spectral Python (SPy), Python Hyperspectral Analysis Tool (PyHAT) and Hyperspectral Python (HypPy).

Feature extraction and reducing the dimensionality of HSI data

Feature extraction is a crucial component for HSI classification. Extracted features, often from multiple data sources, are then used together with classification algorithms for the classification. A major issue with HSI is the high dimensionality of the data producing high spectral correlation and information redundancy that can result in the over-fitting or under-fitting of classification models. The high number of spectral bands is often large compared to the number of training samples resulting in the 'Hughes phenomenon', causing the accuracy of the classifier to decrease. A common strategy to reduce dimensionality is to apply feature reduction extraction or band selection techniques (Vaddi *et al.* 2024, Wu *et al*. 2024). Traditional feature extraction techniques that aim to manage this high dimensionality include the use of Principal Component Analysis (PCA), Minimum Noise Fraction transformation (MNF) and Spectral Indices.

PCA remains widely used for dimensionality reduction and feature extraction (e.g. Peerbhay *et al*. 2013 & 2014). PCA is a linear transformation that projects data onto a new orthogonal feature space that will represent most of the variances in the original data. However, while PCA methods can reduce computer processing, several studies have shown that the PCA dimensionality reduction process can also lose some useful information for individual tree species identification compared with full-band hyperspectral data (Zhang *et al*. 2020, Wu *et al*. 2024).

Peerbhay *et al*. 2013, applied another statistical technique, similar to PCA, called Partial Least Squares (PLS), when classifying eucalypt species in South African plantations using airborne HSI. In PLS, only the most important information from hundreds of wavebands is combined to a few components. The species classification model was then improved by pre-selecting the variables based on the variable importance in the projection (VIP) score. The authors then applied their statistical approach to WorldView-2 multispectral bands where they reported successfully discrimination between *E. grandis*, *E. nitens* and *E. smithii* plantations (Peerbhay *et al.* 2014).

The MNF transformation has also been a commonly applied transformation for feature selection, used to obtain uncorrelated components from HSI data. MNF uses cascaded PCA transformations to separate information and noise. Modzelewska *et al*. (2020), for example, applied MNF-derived bands obtained from airborne HIS data as input to their SVM classification algorithm. Ballanti *et al*. (2018) also obtained MNF bands before evaluating their SVM and Random Forest (RF) classification of tree species in airborne hyperspectral imagery.

Image Classification

While there exist challenges to processing and analysis of HSI, recent advances in analytical workflows and computing capacity permit operational solutions to managing these challenges. Below is a discussion outlining the development of the analytical methods and approaches that have been applied to HSI datasets.

A common classification technique that, in the past, has been applied to multispectral and hyperspectral imagery is the maximum likelihood method. Maximum likelihood classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. In an early study Goodwin *et al.* (2005), using CASI-2 airborne imagery (80 cm pixels, 10 narrow bands from 450 nm – 850 nm), applied a series of supervised maximum likelihood classifications to identify eucalypt species in a moist native forest but was only partially successful, separating out *E. acmenoides* from other eucalypt species. In a further study, Modzelewska *et al*. (2020) applied MNF for feature extraction for the identification of tree species in a Polish forest using airborne hyperspectral HySpex data.

Another popular supervised classification technique applied to HSI data has been the Spectral Angle Mapping (SAM) algorithm. The SAM is a physically based classification method that evaluates the divergence between spectra for each pixel. Its advantages include being relatively insensitive to illumination and albedo effects. For mixed pixels, SAM can also be applied to endmember spectra. Verma *et al*. (2024) successfully applied SAM and the Spectral Information Divergence classifiers to identify five tree species using HSI acquired by the airborne AVIRIS-NG sensor.

A further popular approach to the analysis of HSI has been the application of Machine Learning (ML) non-parametric algorithms, in particular the SVM and RF algorithms. Both these ML algorithms perform well with high dimensional data. Modzelewska *et al.* (2020) successfully applied a Minimum Noise Fraction (MNF) transformation for feature extraction and then an iterative SVM classification to airborne HSI data to produce a thematic map of 7 tree species in a Polish forest. In a study comparing SVM and RF for tree species classification using hyperspectral and Lidar airborne data, Ballanti *et al*. *2016*, reported that neither classifier outperformed the other when using object-based training samples, but that the SVM had higher accuracy when using pixel-based training samples. In a more recent study, Zhong *et al*. (2022) extracted features from a HSI dataset and a spatially co-registered lidar dataset which were then imported into a SVM model for tree species classification.

These ML classifiers have also been routinely applied to remotely acquired, multispectral imagery. For example, Immitzer *et al*. (2019) produced encouraging results using multi-temporal (18 temporal scenes) Sentinel-2 (13 bands) data for mapping 12 tree species (covering 10 tree genera) using a stepwise recursive feature reduction and RF classification. Importantly, however, these ML classifiers by themselves only use spectral information and are based on considering only single pixels at a time and do not support any direct use of contextual image information, which limits their optimal performance (Brandt *et al*. 2025).

Application of Deep Learning algorithms for feature selection and classification

More recently there has been an exponential increase in the application of supervised, deep learning (DL) methods for the analysis of HSI, including the classification of tree species (e.g. Zhong *et al.* 2024). Deep learning has revolutionised the extraction of effective features and classification input data without manual intervention such as the selection of descriptors (Wu *et al*. 2024). The DL models use a series of hierarchical layers to learn directly from training data instead of using expert design features. Numerous studies have demonstrated that when compared with traditional ML methods, DL has more robust self-adaptive and generalisation capabilities and can better handle large-scale complex data (e.g. Hou *et al*. 2023). A common conclusion for many HSI studies focused on tree species classification, is that DL outperforms ML classifiers such as RF (e.g., Sothe *et al*. 2020, Ni-Meister *et al*. 2024).

The most common DL approach has been on the application of various convolutional neural network (CNN) architectures. Initially 2-stage CNNs were evaluated, providing simultaneous acquisition of target class information and pixel-level segmentation within an end-to-end workflow for individual tree species identification. For example, Yao *et al*. (2023) applied a two-stage, Mask R-CNN instance segmentation model using UAV HSI to identify tree species in a planted forest, in Guangxi, China.

More recently, studies that have considered HSI CNN classification methods claim that they can be divided into 3 general approaches, that is, 1D-CNN, 2D-CNN and 3D-CNN, where the number refers to the dimensions of the convolutional kernel (Hou *et al*. 2023, Zhong *et al*. 2024, Zhang & Abdulla 2025). Methods utilising 1D-CNN can extract features from the raw spectral information of pixels to complete classification. Therefore, 1D-CNN models extract only the spectral information and not their spatial information.

The 2D-CNN and 3D-CNN workflows undertake spectral-spatial fusion which combines pixel-level spectral data with neighbourhood spatial context using multi-branch networks or attention mechanisms to extract richer features (Yue *et al*. 2015). More specifically, 2D-CNN based methods first perform feature dimensionality reduction on the hyperspectral images and then extract spatial information in a neighbourhood centred on the pixel to be classified, using a 2D-CNN to complete the classification.

3D-CNNs extract spectral-spatial features simultaneously. These 3D-CNN workflows can extract spatial-spectral features together either within one module or extract the spatial-spectral features separately with different modules (Zhang & Abdulla 2025). Numerous studies have demonstrated that 3D-CNN algorithms are superior in capturing the intricate spatial-spectral features of HSI, leading to improved classification outcomes compared to traditional 2D-CNN methods.

In addition, recent studies are now presenting workflows that combine multiple CNN architectures. Zhang *et al.* (2020), for example, proposed an improved 3D CNN for tree species classification, which uses the raw data of airborne hyperspectral images as input without dimensionality reduction or feature selection and extracted spectral and spatial features simultaneously. A joint spatial spectral feature representation was then turned into a 1D feature as a new input for learning. This 3D-1D CNN model resulted in a tree species classification accuracy of 93% and was shown to be more suited to smaller training samples. This is significant, because while 3D-CNN models can simultaneously learn the local signal changes of the feature cube and classify using the important recognition features, they are very demanding of training data. In another study, Xu *et al.* (2024) using UAV HSI to identify species of hickory, proposed a bimodal CNN structure containing 3D and 2D CNN models as well as introducing a channel attention module to refine the features of the HSI. Many researchers have introduced an attention mechanism into hyperspectral image classification workflows (Hou *et al*. 2023). Xu *et al*. (2024) demonstrated that the accuracy of tree species classification can be improved by introducing an attention mechanism to make the network focus on important features and suppress unimportant features.

However, methods using the 3D convolutional structure can lead to overfitting when the number of network parameters are large. Another way to optimise the full dimensionality of the original data is to use different networks to extract spectral and spatial features separately, then combine the two features to complete the classification. Hou *et al.* (2023) undertook tree species classification from airborne hyperspectral images using a multimodal spatial-spectral network that consisted of a spectral branch and a spatial branch and then feature fusion. In addition, a parameter-free attention mechanism (SimAM) was added to the fusion part of the network. They concluded that this approach produced high-precision tree species classification, out-performing other classification DL methods.

In another study classifying tree species using airborne HSI, Tong & Zhang (2022) applied another kind of DL structure referred to as 'Deep forest' (Zhou & Feng 2019), consisting of a spectral – spatial and cascaded multilayer RF method. Their method adopts two classification stages to fully exploit the spatial information within two kinds of spatial regions: shape-adaptive superpixels (Huang *et al*. 2024) and shape-fixed patches. These two different kinds of spatial information are integrated by concatenating the output of the superpixel-based classification and the spectral features as the input of the patch-based classification. They claim that their approach fully utilizes the available information in high spatial information in airborne HSI and was shown to be more efficient than a 3D-CNN model.

Vision transformers

Vision transformers (ViTs) have recently been trending in image classification due to their promising performance when compared to CNNs (Wang *et al*. 2024b, Zhong *et al*. 2024) including the classification of HSI (Ahmad *et al*. 2026). Vision transformers adapt Transformer architecture initially designed for natural language processing tasks for computer vision by splitting an image into patches, treating them like words (tokens) and using self-attention to understand global (long-range) context. The unique self-attention mechanism of Transformers improves the model's ability to understand global context, enhancing performance in dealing with image noise and scale variations and increasing robustness. Although ViTs often outperform CNNs, they often require larger training datasets and can be computationally intensive due to higher parameters counts.

While at present there are no papers published that specifically apply ViTs to HSI for tree species classification, Shu *et al*. (2025) successfully applied a ViT-based framework that integrates HIS and Lidar datasets for general plant classification. Their dual-branch architecture includes a lightweight ViT that optimizes feature fusion across spectral and spatial dimensions. In another study, Wang *et al*. (2024b) using just RGB images of trees in the genus *Taxus*, successfully applied a dual-branch feature fusion Vision Transformer model, achieving accuracies of > 90%.

Other novel DL approaches are also being evaluated in the remote classification of tree species, including hyperspectral reconstruction. Lin *et al.* (2025) for example, proposed a hyperspectral reconstruction for forested tree species classification based on the CNN algorithm HSCNN and leveraging off multispectral imagery. HSCNN initially 'up samples' an RGB/MS input to a hyperspectral image using a spectral interpolation algorithm. This spectrally up-sampled image has the same number of bands as the expected hyperspectral output. Then, the network takes the spectrally up-sampled image as input and predicts the missing details by learning a stack of convolutional layers.

Hybrid Models

Another recent trend has been the combining of models having different generic architectures. In a hybrid, dual branch approach, for example, models can comprise both a CNN branch and/or a Transformer branch as well as including a ML classifier (Zhang & Abdulla 2025).

Yang *et al*. (2025), for example, proposed a synergistic classification that combined the spatial feature extraction capabilities of deep learning (i.e. a 2D CNN) with the generalization extraction advantages of a machine learning classier (i.e., SVM). Using UAV-based HSI collected from a plantation area in Jiangxi

Province, China, they achieved very high classification accuracies at the tree genus level. Their model also appears to be well suited to smaller reference datasets.

Wu *et al.* (2024) improved their tree species classification using airborne HSI by firstly using an unsupervised band method based on attention mechanisms and then integrating a 3D CNN (=FAST 3D-CNN) for band selection into a few-shot classifier (P-NET). Few-shot learning models, such as the Prototypical Network (P-Net) aim to effectively distinguish classes with a minimal number of samples. Few-shot classification consists of a training phase where a model learns from a large, often open-source, labelled dataset (i.e. transferrable learning) and then undertakes fine-tuning and testing on the smaller target dataset.

Reference datasets

In a comprehensive review of tree species classification from remotely sensed data, Fassnacht *et al*. 2016, emphasised the need to focus on the experimental design, ensuring that the reference/training/validation samples fully represent the population under investigation. Traditionally, training data have been acquired in the field from accurately located plots and/or trees, commonly using a high-precision Global Positioning System (GPS) to measure the location of trees (e.g. Fricker *et al*. 2019). These trees are then identified in the HSI, or spatially co-incident Lidar data. This approach, however, presents challenges, especially when working in closed canopy forests. With the increased application of ML and DL segmentation and classification techniques there has been an increased reliance on image-derived reference datasets for model training and evaluation. This requires annotation of the reference datasets. Unfortunately, image annotation is a labour-intensive process and therefore requires substantial time investment. However, numerous software tools now exist to assist with image annotation, including tools in Arc GIS, QGIS and ENVI (Sandoval-Pillajo *et al*. 2025).

Recently, techniques have been developed that aim to reduce the reliance of DL classification algorithms on large training datasets. Various methods have now been proposed to ameliorate this issue, including data augmentation, transfer learning and few-shot learning (Wu *et al*. 2024). Data augmentation involves generating additional samples from existing data by transforming images through, for example, flipping and rotation (Ma *et al*. 2024).

Transfer learning utilises pre-trained models such as ResNet50 that can learn new tree features and image backgrounds while leveraging information from the existing model weights based on data from a larger generic dataset. That is, knowledge acquired from a large, open-source dataset can be transferred to initialise a model for a target classification dataset having limited samples (He *et al*. 2023).

However, a major impediment to the application of HSI datasets for tree species classification, is the lack of specific reference data for model training and validation. Several open-source, classified HSI datasets are available, such as the 'Indian Pines' HIS dataset which contains a mixture of agricultural and forest elements. More specifically, Schwenke *et al.* (2025) have collated an open-access benchmark dataset for tree species identification in high-resolution aerial imagery (the TreeAI database). At present it focuses on northern hemisphere tree species but could be valuable for pre-training DL models developed for Australian urban tree classification using airborne multispectral imagery.

While several complex DL models have achieved high accuracies in tree species classification using HSI, these workflows have heavy computational and substantial memory requirements. This can now partially be addressed through few-shot learning. This is a machine learning approach where in a training phase the model 'learns' on a relatively large general dataset and then applies an adaption phase where the learned model is adapted to previous-unseen tasks with limited labelled samples. Wu *et al*. 2024, for example, proposed a tree species classification framework using airborne HSI that integrates an optimized 3D-CNN into the backbone of a few-shot prototypical classifer: P-Net.

In another approach to improve tree species classification using HSI and a limited number of training samples, Tong & Zhang (2024) proposed a classification scheme combining SuperPCA and Active Learning (AL). SuperPCA was employed to reduce feature dimensions and harness spectral-spatial information within HIS. Active Learning was employed to select informative samples for the training, thus reducing the requirement for training samples.

Object-orientated approaches for classification vs pixel-based.

Traditional approaches to tree crown delineation have involved local maxima-based techniques (e.g. a watershed segmentation algorithm) using photogrammetric or lidar point cloud data (Durgut *et al*. 2025). Also, in the past, the Trimble software package eCognition was commonly used to segment tree crowns in digital imagery and lidar data (e.g. Ballanti *et al*. 2016, Verma *et al*. 2022).

More recently, DL techniques have been applied for tree crown segmentation. Two approaches exist: object detection, which locates objects within images by drawing rectangular bounding boxes around them and performing instance segmentation (e.g. Mask-R-CNN & YOLO) and semantic segmentation, which classifies every pixel and produces a pixelwise mask with accurate boundaries (e.g. U-Net and DeepLab). In general, object detection DL models are generally faster and less computationally expensive compared to semantic segmentation.

Pixel based DL semantic segmentation models (e.g. U-Net, DeepLab) can distinguish between foreground (e.g. tree crowns and background) of an image. However, issues related to pixel-based classification can include shadowed or spectral noise-filled pixels. Some of the within-pixel variability can be dealt with through spectral unmixing. This approach decomposes mixed pixels into constituent spectra of constituent pure materials (i.e. endmembers) and their fractional abundances. Features associated with endmember spectra can also be extracted from segmented individual tree crowns and included in tree species classification (Pinheiro Ferreira *et al*. 2019).

Unlike pixel-based classification, object detection techniques identify the presence and location of tree crowns and draw boxes around them, whereas pixel-based semantic segmentation classifies every pixel into a predefined class, producing a pixel-wise mask for each classified crown. Deep learning object detection can consist of either two-stage detectors (e.g. Faster R-CNN) which first generate region proposals (bounding boxes) and then classifies them. Single-stage detectors (e.g. You Only Look Once -YOLO) directly predict bounding boxes and class probabilities in a single pass. It has been often argued that object-orientated approaches for HSI classification are more robust for tree crowns (Ballanti *et al*. 2016, Fricker *et al*. 2019, Balestra *et al*. 2024).

Several studies have recently evaluated the benefits of integrating various DL architectures or integrating traditional segmentation techniques with CNNs to improve the accuracy of tree crown detection and segmentation (Durgut *et al*. 2025). For example, both Que *et al*. (2026) and Wang *et al*. (2026) have demonstrated the effectiveness of integrating a YOLO algorithm with Meta's SAM (Segment Anything Model) for accurate crown detection and segmentation.

Another common object-based segmentation approach is to acquire spatially co-incident Lidar data and produce a lidar Canopy Height Model (CHM) to segment tree crowns before structural, textural and HSI spectral features are extracted and inputted into a ML or DL classifier (Vadav *et al*. 2021, Qin *et al*. 2022, Zhong *et al*. 2022, Wang *et al*. 2025). For example, Zhong *et al*. (2022) acquired both UAV-based HSI and lidar data over a mixed tree species forest in northeast China and then delineated individual tree crowns using the Lidar point cloud. Ground training data was obtained by visually matching tree crowns in the images with trees located on the ground. The importance of features extracted from both the HSI and Lidar datasets was analysed by RF. The most influential features were then applied to a SVM algorithm for tree species identification. Semantic segmentation of tree crowns can also be achieved in Lidar CHM applying DL algorithms such as U-Net or DeepLabV3 which masks out non tree crown structures (Wang *et al.* 2024a). Wang *et al*. 2024a then applied a Watershed transform algorithm to further distinguish the connected tree crowns and extract tree crown boundaries.

In a Tasmanian study identifying tree species in a wet eucalypt forest, Yadav *et al*. (2023) reported that their best crown segmentation resulted from a combined MNF dataset derived from airborne HSI and a Lidar CHM. Object-based classification of tree species was then performed using a RF classifier.

Accuracy Assessment and Evaluation Metrics

The accuracy of a model to locate and classify tree species can be evaluated using a set of standard metrics. A common accuracy metric for object detection, including tree crown segmentation, is the 'intersection over union' (IoU), also referred to Jaccards Index. The IoU measures the spatial accuracy of object detection and segmentation by calculating the overlap ratio between predicted and ground-truthed boxes or masks. Several evaluation metrics can then be calculated including precision, recall (= sensitivity or true positivity rate), F1 score and mAP (definitions provided in Wang *et al.* 2026). Semantic segmentation performance can also be evaluated using the same metrics but computed at the pixel level rather than the object level (Wang *et al.* 2026).

A confusion matrix can be also used to summarize classification performance, i.e. class level performance, through examining the numbers of true positives, true negatives, false positives and false negatives. These values can then be used to calculate average and overall accuracies and kappa coefficients, as well as individual user's and producer's accuracies. In their review, Zhong *et al*. (2024) report that the most common metrics for evaluating the tree species classification by CNN models include Overall Accuracy, precision, recall, F1 score and kappa.

Finally, model performance in semantic segmentation can be evaluated through inspection of training and validation loss curves, which plot loss value (discrepancy between the predicted outputs and true outputs) over epochs or iterations (e.g. Wang *et al.* 2026). A decreasing training loss curve that converges to a low value indicates the model is effectively learning from the training dataset while a similar pattern in a validation loss curve assesses how well the model generalizes beyond the dataset. A comparison of the two curves can detect model overfitting or underfitting.

Conclusions

Even though there are challenges associated with the application of HSI for the classification of eucalypt species, significant advances have occurred recently in both image acquisition and subsequent analysis making the task worthy of investigation. Identifying individual tree crowns in closed native forests is much more difficult than distinguishing individual trees in a rural or urban environment. It is assumed that the canopies of established (healthy) plantations should be relatively homogenous and therefore this should reduce spectral mixing in satellite pixels, allowing for tree crown segmentation in higher resolution imagery.

All remote sensing campaigns require coverage over the area of interest and a sampled reference dataset for model calibration and validation. As eucalypt plantations are located in several regions of NSW and the aim is to characterise these plantations including species composition, it is recommended that an evaluation of satellite HIS be undertaken to determine its suitability for this task. The traditional HSI satellites such as EnMAP have a spatial resolution of 30 m resulting in spectrally mixed pixels. However, very recently several HSI satellite systems have been launched having much lower spatial resolution, i.e. 5 m. This includes Pixxel's Firefly hyperspectral constellation and the South Australian HyperScout2 sensor on the Kanyini satellite.

Advanced modelling of HSI requires adequate labelled reference data for training and validation. There are several approaches to the acquisition of this information. For NSW, this could include using FCNSW hardwood plantation datasets and recently edited plantation maps which have identified the location of eucalypt plantations but not at the species level (pers comm. Masoomeh Alaibakhsh, DPIDR Forestry Research). In areas where this information is absent or not accurately identified, e.g. on private property, there may be a requirement to acquire airborne HSI supported by on-ground inspections. There are both commercial and academic providers of airborne HSI in Australia. The associated costs and working relationship will differ between providers. Costs would also be influenced if it was considered that fusion with other sources of spatial data was considered valuable, such as Lidar.

Finally, an overall decision needs to be made as to how much of the data processing and analysis should be undertaken 'in-house'. Even if an 'in-house' approach was desirable then the purchase of specialist HSI software such ENVI needs to be considered.

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