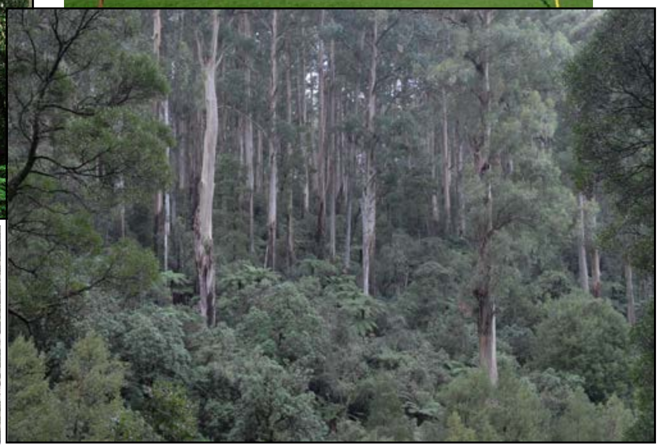
Australian Woody Vegetation Landscape Feature Generation from Multi-Source Airborne and Space-Borne Imaging and Ranging Data (CRC-SI 2.07)



Deliverable 1. Literature review for determining optimal data primitives for characterising Australian woody vegetation and scalable for landscape-level woody vegetation feature generation.

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This document has been created in the context of the CRC-SI 2.07 project Australian Woody Vegetation Landscape Feature Generation from Multi-Source Airborne and Space-Borne Imaging and Ranging Data

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3 Introduction

This review seeks to define and document a suite of data primitives useful in describing woody vegetation. The ultimate outputs of the research will be to identify landscape level woody vegetation features (i.e. spatial layers) from field and remote sensing scaled-up woody vegetation data primitives. The generated landscape features will be designed to be highly correlated with end user land manager landscape metrics. As such these data primitives need to make sense as functional descriptors at a landscape scale and be scale-able (i.e. function in a similar manner at a range of spatial scales from the plot to community to landscape / catchment). Lastly, given that this research is set in an Australian context the data primitives must have utility in Australian sclerophyll environments.

The purpose of data primitives, in the context of CRC-SI project 2.07, is as a universal set of functional descriptors which are recoverable both as field-measured variables and have an analogue remotely sensed equivalent. The remote sensing of the data primitives consists of the spatial assessment of those descriptors. For example, discolouration can be mapped as average foliage pigment content and canopy height can be represented spatially as average height of the dominant trees within a spatial unit. These data elements or primitives can be later compiled into features and assembles useful for land management decision making. Moreover, several of these indicators can be grouped into cohorts i.e. chemical composition and Discolouration; stem density and basal area etc.

This document presents a literature review of the following selected data primitives:

- Canopy height
- Tree diameter
- Tree spacing
- Vertical structure
- Forest cover and leaf area
- Tree species composition
- Course woody debris
- Foliage chemical composition

These variables have good resonance with the needs analysis for the assessment of the 28 biological indicators (as described by the Santiago Declaration at the sixth meeting of the Montreal Process Working Group (Montreal Process Working Group, 1995), see Appendix A for a full overview).

To canvas the opinion of land management agencies (both federal and state), a web-based survey was conducted targeting key personnel involved in land management in Australia and New Zealand. The survey objectives were firstly, to better understand the needs of land managers for decision and policy making; and, secondly, to gain feedback on the types of metrics commonly used in forest attribution. The survey was sent to 81 people; with 32 completions during May 2012 –summary results presented here. For a full report on this survey please see appendix B.
When asked “What are the five most important forest metrics to capture using remote sensing from a forest management perspective?” the top ten most popular metrics (of 31) were:

- Tree height
- Forest condition and health
- Density of tree crowns (LAI or FPC)
- Species/type mapping
- Change detection
- Forest cover extent
- Fire frequency and severity
- Vertical foliage density profile
- Biomass/Carbon
- Basal area

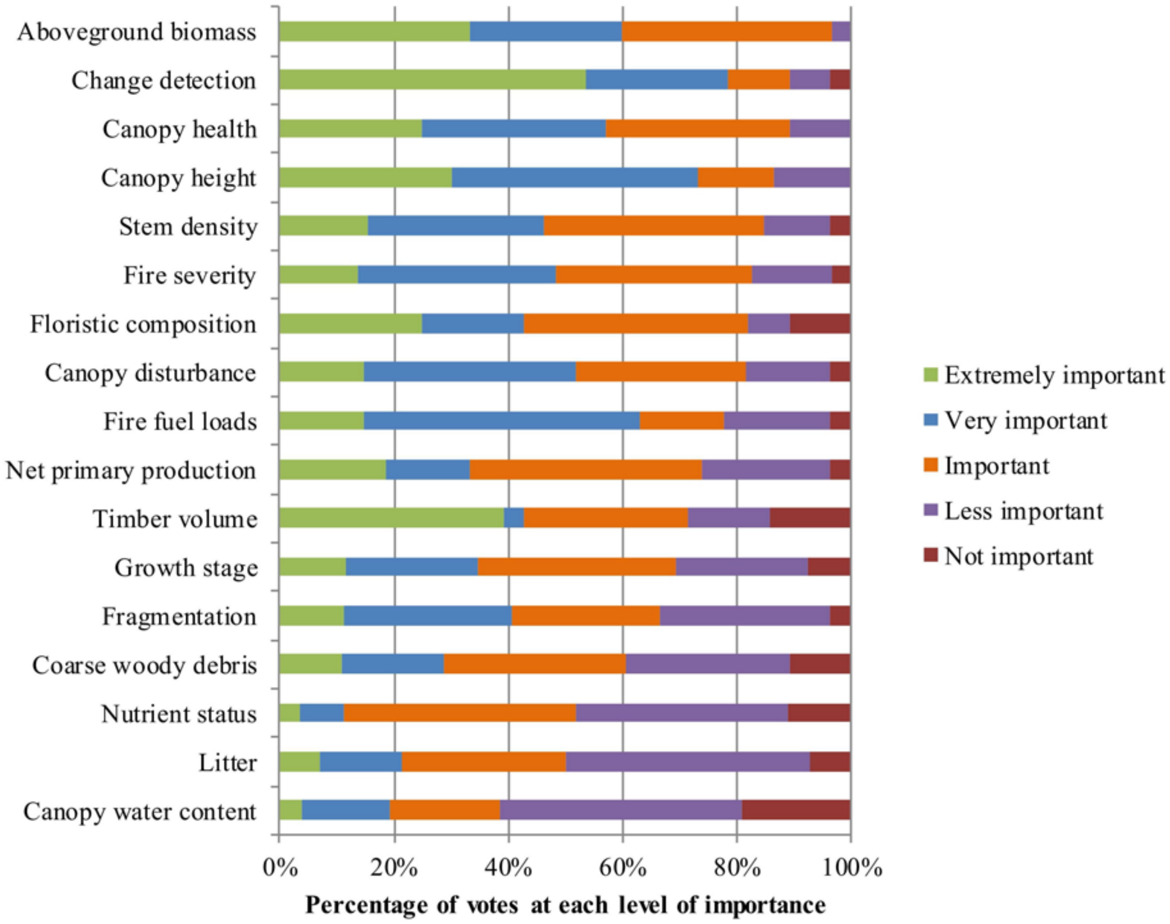

Figure 1. Importance of the forest management metrics according to land management agents participating in the web survey.

Respondents also ranked the importance of seventeen of these metrics from a forest management perspective (Figure 1).

As a final indicative (not definitive) appraisal, a rudimentary analysis of key words cited in the recent peer-reviewed literature was undertaken (Table 1). Leaf area, canopy cover, chlorophyll content and basal area are the most common key words. Google scholar was used as a search engine in order to consider not only ISI journal publications but also governmental agencies/management reports and conference proceedings.

Based on these assessments the following review of data primitives is presented. Seven key areas were focussed on Canopy height, Stem density, Overstorey/Understorey, Leaf area and Canopy cover, Forest typology/Floristics, CWD and Chlorophyll content.

Table 1. Number of reported articles using data primitive key words since 2011 (Global & Australian studies); source Google scholar 12th September 2012.

Data primitive	**Global**	**Australian context**
Course Woody Debris	1,850	588
Forest typology	64	12
Forest classification	732	130
Leaf area*	17,500	4,070
Canopy cover*	5,140	1,650
Understory / overstory	0	0
Canopy height	3,180	982
Stem density	1,660	502
Basal area	5,640	1,260
Chlorophyll content	7,480	1,110

In the following sections the main woody vegetation data primitives are defined. The characterisation of those data primitives is presented together with methodologies and applications for their measurement in the field and their spatial assessment through remote sensing. Finally, a section addressing specific studies in the Australian environment is included for each of the data primitives presented.

4 Metrics for woody landscape attribution

4.1 Canopy height

4.1.1 Definition

The height of a standing individual tree can be defined as the vertical distance from ground level to its uppermost point (Empire Forestry Association 1953) or to the top of the live crown (Zimble *et al.* 2003). Canopy height is a metric describing the statistical aggregation of individual tree heights for a region (Parker 1995).

4.1.2 Characterisation

An assessment of the height of all individual trees at a landscape level is inherently unfeasible (Magnussen & Boudewyn 1998) and an aeral generalisation of individual tree heights is estimated. Canopy height is considered important in forest planning (Næsset 1997) and is a key criteria in the United Nations (UNFCCC 2002) and Australian (National Forest Inventory 1998) definitions of forest at a landscape level; applied uses of canopy height are listed in Table 2. Canopy height can be regarded as a categorical (Mellor *et al.* 2012) or continuous variable and is scale independent, being reported at the plot (Lovell *et al.* 2003; Means *et al.* 1999), stand (Næsset 1997), regional (Hudak *et al.* 2002) and global scale (Simard *et al.* 2011; Lefsky 2010). Canopy height at extents beyond the plot are often reported as a 3-dimesnoinal canopy height surface model (CHM).

Mean canopy height can refer to either the mean height of all trees within a defined extent or an objectively selected subsample (Næsset 1997). The commonly used “dominant height” is defined as the mean height of all trees that are not overtopped and whose crowns are not shaded by adjacent trees (Lefsky *et al.* 1999a). Terms that are synonymous with dominant height tend to differ with regard to the sample size/area used, for example, “predominant height” is defined by Lewis *et al.* (1976) as the tallest 100 trees per hectare whereas “top height” is the tallest 75 trees per hectare Lovell *et al.* (2003), however these definitions may include trees that are not strictly (co)dominant. Cohen & Spies (1992) defined the “upper canopy” as all co-dominant, dominant and emergent trees. Maximum height and top-of-canopy are terms used particularly with regard to LiDAR and derivation of CHM. A common forestry term for canopy height used in north America and Scandinavia is “Lorey’s height” (h_L); that is the basal area weighted mean canopy height (Næsset 1997), it is calculated as in [1]. Lorey’s height gives more weight to larger trees that have greater influence on canopy height (Lim *et al.* 2003).

$$h_{\mathrm{L}} = \frac{\sum_{i=1}^{n} h_i a_i}{a} \quad [1]$$

4.1.3 Methods and application

Tree height has been traditionally assessed from the ground (Figure 2), utilising instruments such as a clinometer, electronic total station or a hypsometer (Hollaus *et al.* 2006). Canopy height is then estimated as a mean of all or a subsample of trees measured, canopy height is therefore a funtion of plot or subsample size (Lovell *et al.* 2003). With the emergence over the passed three decades of radar, optical and airborne laser scaning (ALS e.g. LiDAR) remote sensing technologies, the ability to accurately assess vertical canopy structure over large spatial extents has become reality (Hudak *et al.* 2002; Sexton *et al.* 2009). Reviews of remote sensing applications for canopy height estimation are provided by Wulder (1998), Lim *et al.* (2003) and Wulder *et al.* (2008). This review will focus on canopy height from field plot and ALS due to their applicability to project 2.07.

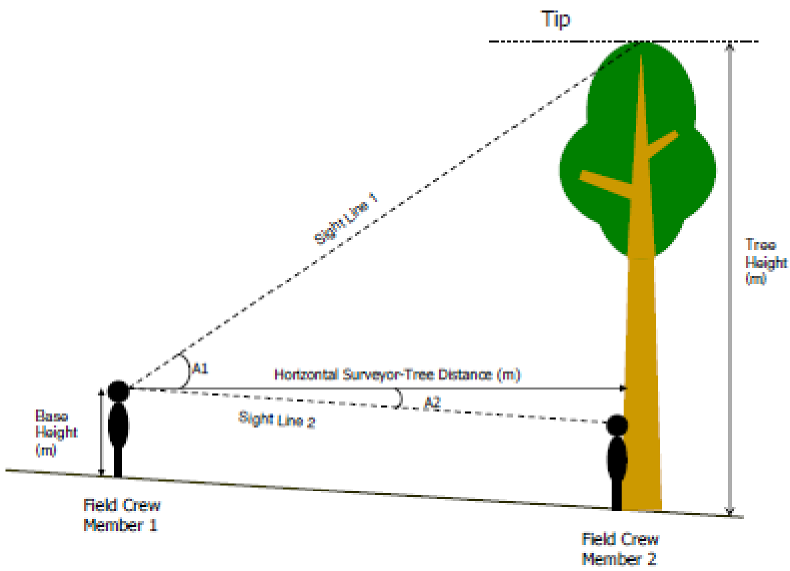

Figure 2. Triganmonetrical principles of tree height measurement (Victorian Department of Sustainability and Environment 2012).

Height estimates synonymous with mean, dominant height and Lorey's height can be derived from small-footprint discrete-return airborne laser scanners (ALS). For example, Popescu *et al.* (2002) defined mean height as the arithmetic mean of all first returns above a vertical threshold of 2.44 m. Næsset (1997) calculated the square of height values for individual non-ground returns to report a weighted mean canopy height analogous with Lorey's height. It is generally accepted that ALS is a more accurate method for height determination than other methods (Næsset & Økland 2002; Tickle *et al.* 2006). However ALS can underestimate canopy height; as a pulse may not interact with the apex of the tree (Lim *et al.* 2003; Hyyppä *et al.* 2008); the amplitude of energy reflected from "soft" leafy targets may not be sufficient to exceed an arbitrary threshold to record a return (Lovell *et al.* 2003); and the effect of wind on the top of the canopy at the time of capture (Tickle *et al.* 2006). Conversely, overestimation may be caused by emergent trees (Lovell *et al.* 2003). Accuracy at the edge of a swath may also diminish as a result of uneven point spacing (Lovell *et al.* 2005).

A number height statistics can also be derived from large-footprint full-waveform ALS that are synonymous with mean and dominant height. In a single waveform return, the point at where sufficient return energy triggers the sensor to begin recording to the modal peak of the last (ground) return is equivalent to vertical canopy height for a measured footprint (Lefsky *et al.* 1999a; Means *et al.* 1999). RH100 (Ni-Meister *et al.* 2010) and CHP100 (Drake *et al.* 2002) i.e. the height at which 100% of foliage volume is located below, are synonymous with vertical canopy height. When referring to aggregated footprints, Lefsky *et al.* (1999a) defined mean height as the mean of vertical canopy height for 5 x 5 returns. Simard *et al.* (2011) utilised RH100 when reporting canopy height at a global scale; this was validated against predominant height i.e. the 3 tallest trees in 1600 m^2 plot.

Table 2. Applied uses of canopy height as a data primitive

Application	Context	Citation
Forest Biomass	Global	Lefsky *et al.* (2001); Drake *et al.* (2002); Hurtt *et al.* (2004); Patenaude *et al.* (2004); Asner *et al.* (2010); Koch (2010); Swatantran *et al.* (2011); Hudak *et al.* (2012);
	Australia	Lucas *et al.* (2008b)
Habitat	Global	Goetz *et al.* (2007); Hyde *et al.* (2006); Hinsley *et al.* (2009); Hill & Thomson (2005)
	Australia	Brown (2001); Haywood & Stone (2011)
Species/Floristics/cover	Global	Hill & Thomson (2005)
	Australia	Tickle *et al.* (2006); Burgman (1996); Mellor *et al.* (2012); Zhang & Liu (2012)
Resource management / forest inventory	Global	Næsset (2007); Næsset (1997); Wulder *et al.* (2008)
	Australia	Lim *et al.* (2011); Turner (2007); Brack (2007)

4.1.4 Australian context

Definitions of field assessed dominant, predominant and top height vary across Australia. For example the number of trees included in dominant height estimation in NSW and the ACT is 40 trees ha^{-1}, in QLD is 50 trees ha^{-1}, in SA is 75 trees ha^{-1} (Research Working Group #2 1999). Studies reporting canopy height tend to utilise small foot discrete return ALS (Table 2) and in this regard dominant height has been calculated as the arithmetic mean for a subset of highest returns (Lovell et al. 2003; Lee and Lucas 2007) or a percentile of all returns i.e. 99th percentile (Jenkins 2012) or 95th percentile (Haywood and Stone 2011). Tickle *et al.* (2006) calculated dominant height for a plot as the mean height of the tallest trees within subplots which they then scaled to a regional level stratified by forest type. Goodwin *et al.* (2006) found a good agreement with maximum return height and maximum observed tree height at the plot scale. Using the satellite-borne ICESat full-waveform LiDAR data to assess canopy height at a continental scale, Lee *et al.* (2009) found the height from the centre of the ground pulse to the centre of the first vegetation pulse (centroid height) was synonymous with ALS derived predominant height. Mellor *et al.* (2012) defined canopy height using a classification system e.g. low, medium and tall, derived from aerial photography interpretation.

4.2 Tree diameter and volume

4.2.1 Definition

The tree diameter and volume are important structural components related to stand age and aboveground biomass. Tree diameter is generally measured during plot-based inventories in the form of Diameter at Breast Height (DBH). In these inventories, usually only trees larger than a threshold DBH (e.g. 5 or 10cm) are included in the survey. The stand mean DBH is the average DBH of all surveyed trees in area, often expressed in centimeters. There is no widely agreed upon definition of tree volume and it varies with the purpose of the inventory. Possibly, the most logical and general definition is: the volume of stemwood from the root collar to the top (Zianis *et al.* 2005). Stemwood is the main part of the tree (excluding branches and roots). The stand volume, expressed in m^3 per area unit, is the combined stemwood volume for all trees within an area.

4.2.2 Characterisation

Mean DBH can be used to characterize the general tree size within an area or stand. It needs to be used in conjunction with other plot attributes since it does not convey information about the number of trees or total stand volume. There are a number of area-based metrics that can be derived from the DBH of all trees within an area. These include mean DBH, quadratic mean stem diameter, stand basal area, variation in DBH, and number of large trees.

Historically in forestry, the mean diameter sometimes refers to the quadratic mean square diameter (QMSD). QMSD is calculated with equation [2].

$$QMSD = \sqrt{\frac{\sum d_i^2}{n}} \qquad [2]$$

where d_i d_i is each individual tree and n the number of trees (Curtis and Marshall 2000). QMSD can be regarded as a more informative attribute than the arithmetic mean DBH because it is more closely related to stand volume (Gómez *et al.* 2012). It is related to mean basal area and gives higher weight to larger trees.

Stand basal area is the cumulative basal area of all stems in a plot expressed in m^2/ha. It is closely related to stand volume and biomass. Jonson and Freudenberger (2011) found strong relationships between stand basal area and stand biomass for mixed forests in south-western Australia. Importantly, they determined that generic allometric relationships across species could be justified. Basal area is also related to forest age and has been used for identification of old growth forests. A study by Ziegler (2000) determined that basal area, as well as mean DBH, increased with stand age in a hemlock-hardwood forest. Stand volume can be calculated from basal area, sometimes in combination with tree height, using species-specific allometric equations. It is related to above-ground biomass, carbon, and timber resources.

The diversity of tree sizes in a plot can be used as an indicator of the variability of succession stages within a stand, and has been linked to structural complexity (Zenner 2000), the potential to generate woody debris (Spies 1998), and biodiversity (Van Den Meersschaut and Vandekerkhove 2000; Neumann and Starlinger 2001). It can also be seen as a record of past disturbances and is informative for decisions about thinning or harvesting of the forest (Spies 1998). This metric is often quantified by the standard deviation of tree DBHs (SDDBH) [3].

$$SDDBH = \sqrt{\frac{\sum_{i=1}^{n}(d_i - \bar{d})^2}{n-1}} \qquad [3]$$

where d_i is tree DBH and $\bar{d}$ is the arithmetic mean DBH.

The number of large trees can be derived from an inventory of DBH of all trees in a plot. It is another metric of relevance as an indicator of old-growth forests (Spies and Franklin 1991), and for identifying habitats for fauna that depend on large trees for survival (Gibbons *et al.* 2002). The definition of large trees varies between different studies and the ecosystem that is inventoried. Spies and Franklin (1991) used DBH > 100cm in a Douglas-fir forest in western USA. Van Den Meersschaut and Vandekerkhove (2000) defined large trees as 40cm ≤ DBH < 80cm, and trees with thicker stems were defined as very large, in a temperate Belgian forest.

4.2.3 Methods and applications

There is a wide range of applications for tree diameter derived attributes, both for timber production and conservation purposes. These are summarised in Table 3 and include estimates of biomass and carbon, identification of successional stages, and mapping of wildlife habitats.

In field based inventories, tree DBH is usually measured with a tape outside the bark. Inventory protocols guideline how to measure the DBH for different stem forms (Figure 3). Tree volume can be estimated from DBH and/or height using allometric equations (Zianis *et al.* 2005).

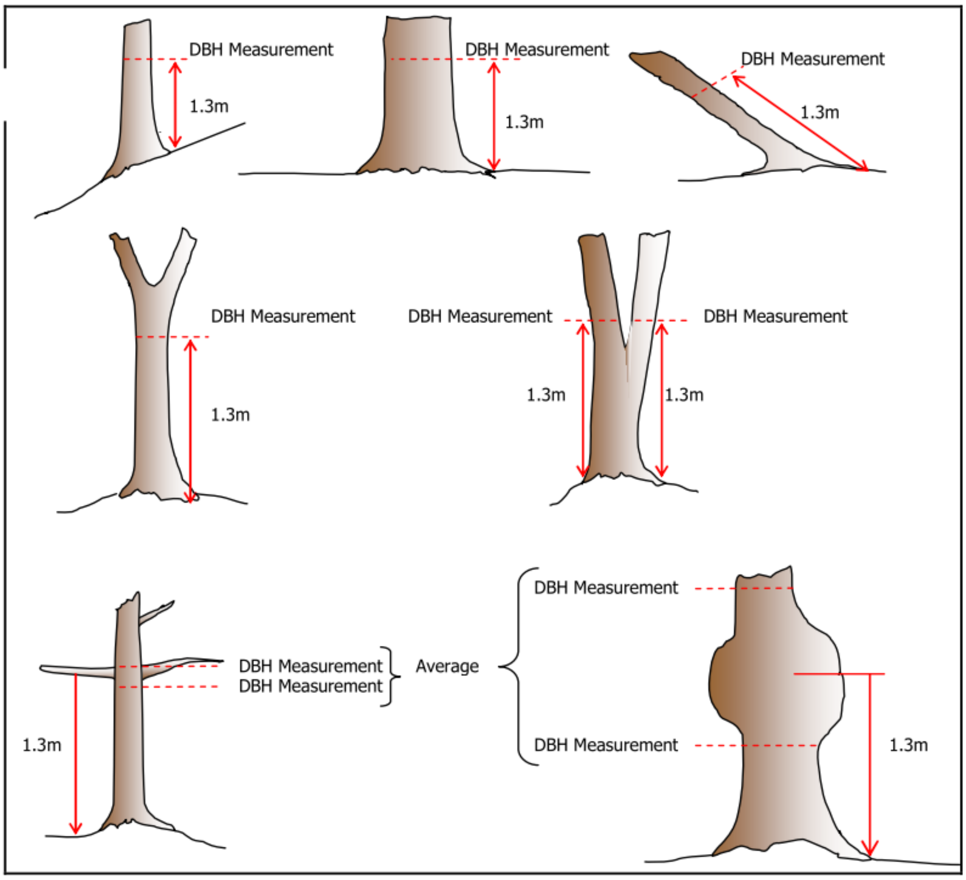

Figure 3. Example of rules for DBH measurements for different stem forms (DSE, 2012).

Table 3. Applications of tree diameter and volume metrics.

Application	Forest metric	Reference
Forest age and successional stages	Stand basal area	(Ziegler 2000; Kanowski *et al.* 2003; Woinarski *et al.* 2004)
	Mean DBH	(Ziegler 2000)
	SDDBH	(Spies and Franklin 1991; Wimberly and Spies 2001)
	Number of large trees	(Spies and Franklin 1991; Wimberly and Spies 2001)
Biomass and carbon	Stand basal area	(Jonson and Freudenberger 2011; Asner *et al.* 2012)
Timber yields	Stand basal area	(Means *et al.* 2000; Burkhart and Tomé 2012)
	Stand volume	(Maltamo *et al.* 2004; Tonolli *et al.* 2011)
Disturbance	Stand basal area	(Smiet 1992; Bhat *et al.* 2000; Bhuyan *et al.* 2003)
Biodiversity	SDDBH	(Van Den Meersschaut and Vandekerkhove 2000; Neumann and Starlinger 2001)
Wildlife habitat	Number of large trees	(Gibbons *et al.* 2002)

From a remote sensing perspective, there have been several attempts to model structural parameters using medium resolution spaceborne data such as Landsat and SPOT (Cohen and Spies 1992). In the last decade, LiDAR has been the dominant technology because of its ability to model vegetation structure in three dimensions. Of the DBH based metrics, basal area, mean DBH, and stand volume are the most commonly estimated in the remote sensing literature. In area-based inventories, a number of LiDAR metrics are derived from the point cloud and regressed against field data in order to find empirical relationships. Often height percentiles, cover percentiles, density percentiles, and their standard deviations are the most informative LiDAR metrics for modelling basal area and volume (Means *et al.* 2000; Holmgren 2004; Ioki *et al.* 2010; Yu *et al.* 2010). There have also been attempts to use data from high-spatial-resolution satellite sensors, such as Worldview2 and Quickbird, for estimating these attributes (Ozdemir and Karnieli 2011; Gómez *et al.* 2012). These studies rely on a set of textural features (e.g. entropy and contrast) for explaining the variation in structure.

SDDBH and number of large trees are generally not estimated from remote sensing data, possibly because they are difficult to estimate. However, Ozdemir, and Karnieli (2011) showed that SDDBH could be mapped for an Israeli dryland plantation forest using high-spatial resolution WorldView-2 imagery. For estimation of the number of large trees using LiDAR, it is necessary to apply an individual tree identification approach and estimate both location and size of trees. This requires both high point cloud densities and computing-intensive algorithms which might not be economically feasible to scale up to very large areas.

4.2.4 Australian context

In Australian landscapes, studies on estimating stand volume and DBH-based metrics using LiDAR data have so far mainly focused on plantation forests. Musk (2011) estimated basal area (r^2=0.75) and merchantable stand volume (r^2=0.84) in a Tasmanian eucalypt hardwood plantation, and Turner *et al.* (2011) estimated stand volume (r^2=0.81 to 0.83) for a pine plantation in New South Wales. One example of LiDAR-based estimation of basal area in a natural eucalypt forest is the study by Haywood and Stone (2011). They found that the 50th height percentile and intensity values were useful for predicting basal area (r^2=0.56). Applications of LiDAR for wood resource mapping are expected to continue growing and developing in the coming years (Turner *et al.* 2011). Studies on estimating biomass in native forests (e.g. Lucas *et al.* 2006) have generally not estimated basal area or stand volume. Instead, biomass has been predicted directly from various LiDAR metrics.

4.3 Tree spacing

4.3.1 Definition

Tree spacing refers to the number and spatial arrangement of stems in an area. The density of stems is the most commonly inventoried metric in this category. It is measured in number of stems per area unit. Generally, there is a minimum DBH (e.g. 5 or 10cm) and/or height for the stems included in the field inventory.

4.3.2 Characterisation

Stem density is related to stand age and is often negatively correlated with mean DBH (Spies and Franklin 1991; Acker *et al.* 1998). It is a measure of site occupancy and is central for modelling growth and yield projections, and to guide decision-making about the need for thinning (Næsset and Bjerknes 2001). From a silvicultural perspective, it has long been important to estimate the degree of stand competition in order to apply thinning operations before natural self-thinning occurs. Based on stem density and a metric for tree size (e.g. DBH), it is possible to estimate the stand stocking level. *Stocking* refers to the number of trees in relation to an optimal number set by some management regime (Burkhart and Tomé 2012).

Stem density does not convey information about the spatial arrangement, or clustering, of trees. The degree of clustering is important because it can reveal information about forest growth processes and competition (Pretzsch 1997). The Clark-Evans Index (Clark and Evans 1954) is perhaps the most commonly utilised metric for these patterns (McElhinny *et al.* 2005). It measures the ratio between the observed average distance $\overline{r}_{obs}$ from a tree to its nearest neighbour and the expected average distance $\overline{r}_{\exp}$ based on a randomly distributed tree population [4]

$$R = \frac{\overline{r_{obs}}}{\overline{r_{\exp}}} = \frac{\left(\frac{1}{n}\right)\sum_{i=1}^{n} r_i}{0.5\sqrt{\frac{10000}{N}}} \qquad [4]$$

where r_i r_i is the distance from tree i i to its nearest neighbour, n is the sample size, and N N is the number of trees per hectare (Clark and Evans 1954; Ozdemir and Karnieli 2011).

4.3.3 Methods and applications

Applications of tree spacing are summarised in Table 4. While they can be important for silvicultural purposes, they are mainly used in conservation and forest condition applications.

While there were early attempts to estimate stem density using Landsat and SPOT data (Cohen and Spies 1992), most recent studies use LiDAR technologies. The local maxima in a LiDAR-generated Canopy Height Model (CHM) (Persson *et al.* 2002), or the horizontal and vertical density of points in the LiDAR point cloud (Lee and Lucas 2007), can be used to identify individual tree locations. Stem density has also been derived using statistical distribution-based methods from either LiDAR metrics (Næsset and Bjerknes 2001), or textural attributes of optical imagery (Klobucar *et al.* 2011; Ozdemir and Karnieli 2011). Tree clustering is seldom estimated using remote sensing, but it can be computed from any dataset that permits identification of individual trees. Another approach, exemplified by a study by Ozdemir and Karnieli (2011), is to derive it statistically using textural features from high-resolution optical imagery.

Table 4. Applications of tree spacing

Application	Forest metric	Reference
Successional stages and old-growth forests	Stem density	(Spies and Franklin 1991; Acker *et al.* 1998; Kanowski *et al.* 2003; Woinarski *et al.* 2004)
Growth prediction and stocking	Stem density	(Næsset and Bjerknes 2001; Burkhart and Tomé 2012)
	Clark-Evans Index	(Pretzsch 1997)
Fire risk and severity	Stem density and clustering	(Richardson and Moskal 2011)
Disturbance	Stem density	(Bhat *et al.* 2000; Bhuyan *et al.* 2003)
Input to physical canopy models	Stem density	(Chen and Leblanc 1997; Zarco-Tejada *et al.* 2004)

4.3.4 Australian context

Both individual tree and area-based approaches have been used in Australian forests. Haywood and Stone (2011b) used the area based approach and found that a model based on height percentiles, intensity, and skewness, derived from the LiDAR point cloud, could predict stem density reasonably well (r^2=0.41). Turner *et al.* (2011) compared the individual tree and area-based approaches on a pine plantation in New South Wales with good results for both. Stem density was estimated with r^2 of 0.85 and 0.88 for the area based and individual tree based approaches respectively. Another area-based study (Musk 2011) mapped stem density in a Tasmanian eucalypt hardwood plantation using a Random Forests (RF) algorithm with an r^2 of 0.64. That is weaker than the same study's results for basal area (r^2=0.75), mean dominant height (r^2=0.96), and stand volume (r^2=0.84). Stem density is a comparatively difficult attribute to estimate, and it is particularly hard in ecosystems characterised by complex vegetation structures (Richardson and Moskal 2011). The native Australian sclerophyll forest is one such example. Here, trees are often clustered and there is sometimes a layer of more shade-tolerant trees underneath the dominant canopy. These characteristics make it difficult to identify individual trees in the CHM. Lee and Lucas (2007) developed the Height-Scaled Crown Openness Index (HSCOI) as an alternative method for identifying trees in more complex forests. It identifies trees based on the vertical and horizontal density of points in the LiDAR point cloud. They obtained good results at a Queensland study site composed of mixed species woodlands and open forests. About 70-80% of stems (DBH ≥ 5cm) were correctly located. The accuracy was lower when the same method was applied on a denser and more structurally complex forest in northeast Victoria.

Kandel *et al*. (2011) proposed another methodology based on the assumption of a direct relationship between mean DBH and stem density. They estimated stem density in Victorian native sclerophyll forests. First, mean DBH was calculated based on an allometric relationship with mean canopy height estimated using LiDAR. Then, stem density was derived from mean DBH using a formula for tree competition. According to the authors, the results are promising for operational applications in Australian forestry. However, a strong correlation between mean DBH and stem density cannot be taken for granted. One of their two study areas exhibited a strong relationship (r^2=0.97), and the other a weaker correlation (r^2=0.52). Other literature suggest that the relationship between tree size and density is less straightforward, varying with age composition, species composition, and the degree of exogenous disturbances (Coomes *et al.* 2003).

4.4 Vertical structure

4.4.1 Definition

Forest vertical structure can be defined as the as the configuration in space and time of vegetative components in terms of position, extent, quantity, type and connectivity, from the canopy top to forest floor (Brokaw & Lent 1999; Parker 1995).

4.4.2 Characterisation

Forest vertical structure can be characterised by configuration of vegetative layers i.e. presence/absence of understorey (Morsdorf *et al.* 2010; Hill & Thomson 2005). Presence/absence analysis can be applied to a three-dimensional domain where voxels are assigned to either containing a void or vegetation (Lee *et al.* 2004; Lefsky *et al.* 1999a). Count of vegetation layers within a vertical profile has been used to identify the presence of an understorey (Maltamo *et al.* 2005) and inference of single- or multi-layered forest has been achieved by determining variance in height of all trees within a plot (Zimble *et al.* 2003). For a plot, vertical structure has been described using foliage height profiles (FHP) (MacArthur & Horn 1969), that is the cumulative percentage cover as a function of height. FHP is a function of gap probability vertically through the canopy [5];

$$\mathrm{FHP_c}(h) = -\ln(1 - \mathrm{cover}(h)) \qquad [5]$$

where $\mathrm{FHP_c}(h)$ is leaf area index expressed as a fraction of projected ground area above height *h*, and cover(*h*) is the fraction of sky obscured by foliage above *h* (Lefsky *et al.* 1999a). This assumes a uniform leaf angle and a radom distribution of leaves through the canopy which may not be the case (Lovell *et al.* 2003; Jupp *et al.* 2008). Full descriptions of vertical profile derivation are provided by Ni-meister *et al.* (2001) and Lovell *et al.* (2003). Terms synonymous with FHP include canopy height profile (CHP) that includes all woody and foliage elements thought the canopy (Lefsky *et al.* 1999a; Harding *et al.* 2001); “actual” and “apparent” foliage density profiles, the latter as a result of ALS being unable to resolve leaf-angle distributions and clumping i.e. non-random leaf distribution (Ni-meister *et al.* 2001); canopy height distributions (CHD) and canopy height quantiles (CHQ) (Zhao *et al.* 2009); and verticle canopy profiles which represent the vertical distribution of crown volume (Drake *et al.* 2002). As presented in Table 5, a metric of vertical height is utilised widely in applied forest science and can be considered of greater importance than canopy height (Goetz *et al.* 2007).

Table 5. Applied use of vertical structure as a data primitive

Use	Location	Citation
Forest Biomass	Global	Drake *et al.* (2002); Zhao *et al.* (2011); Lefsky *et al.* (1999b); Lefsky *et al.* (2001); Næsset (2004)
	Australia	Fensham *et al.* (2002); Lucas *et al.* (2008a)
Habitat	Global	Goetz *et al.* (2007); Turner *et al.* (2003); Graf *et al.* (2009); Ferris & Humphrey (1999)
	Australia	
Floristics	Global	
	Australia	Zhang & Liu (2012); Miura & Jones (2010); Lucas *et al.* (2008a)
Resource management / forest inventory	Global	Morsdorf *et al.* (2010); Næsset (2004)
	Australia	

4.4.3 Methods and applications

Methodologies to identify multi-layered forests or estimate vertical profile include using a calibrated telephoto lens (MacArthur and Horn 1969) or laser range finder (Radtke and Bolstad, 2001) to measure distances to first leaf interception. With regard to remote sensing, stereo photogrammetry interpretation (Fensham *et al*., 2002), radar (Hyyppä *et al*., 2000), terrestrial LiDAR (Parker *et al*., 2004) and discrete (Lovell *et al*., 2003) and full-waveform airborne laser scanning (Means *et al*., 1999) have been applied to vertical structure determination. The MacArthur and Horn (1969) method uses a calibrated telephoto lens to determine multiple measurements of distance to first leaf interception, this method is still widely used as a validation technique (Lefsky *et al*., 1999a; Lovell *et al*., 2003).

Discrete return ALS derived statistics of height such as standard deviation and percentiles can provide information on vertical structure, even utilising systems restricted to recording first and last returns (Popescu *et al*., 2002; Lovell *et al*., 2003; Magnussen and Boudewyn, 1998). A laser pulse may not necessarily interact with the top of the canopy and therefore utilisng all returns will elicit information from within and below the canopy (Magnussen and Boudewyn 1998; Maltamo *et al*., 2005). Næsset (2004), for example, utilised height percentiles in a stepwise multiple regression to estimate forest inventory variables including biomass. Discrete return ALS has also been used to determine vertical profile and density profiles (Lovell *et al*. 2003; Coops *et al*. 2007). This method calculates the probability of a gap from the top of the canopy to a given height (z) and compares this to the total number of LiDAR pulses [6];

$$P_{gap}(\mathbf{z}) = \frac{\left(\#z_j \middle| z_j > z\right)}{N} \qquad [6]$$

where $\#z_j$ is the number of returns above z z and N N is the total number of laser pulses. The cumulative projected foliage area index is then calculated by a modified exponential transformation (Aber, 1979) of *(1-Pgap(z))* $1 - P_{gap}(\mathbf{z})$ [7];

$$L(z) = -\log(P_{gap}(z)) \qquad [7]$$

where the derivative of *L(z)* is the foliage profile (Lovell *et al*. 2003). To stabilise *L(z)* a distribution function can then be fitted, for example a Weibull function [8] where *H* is maximum canopy height and *α* and *β* are fitted parameters (Lovell *et al.,* 2003; Jaskierniak *et al.,* 2011; Coops *et al.,* 2007). Coops *et al.* (2007) fitted Weibull distributions to canopy profiles derived from point quadrat, inventories and LiDAR data; they noted a good agreement between Weibull parameters (*α* and *β*) and mid crown depth as a ratio of total height and crown length respectively.

$$L(z) = 1 - \left[e^{-\left(\frac{1-\frac{z}{H}}{\alpha}\right)^{\beta}} \right] \qquad [8]$$

The authors concluded that LiDAR can be used to derive a vertical canopy profile and that bi-modal distributions are required for multi-layered forests. Riaño *et al*. (2003) applied a cluster analysis to multi return system to delineate between canopy and understorey; first aggregating the discrete return to create a canopy density profile and then applying an exponential transformation to account for shadowing of the understorey.

Full waveform LiDAR has also been used to characterise vertical structure (Lefsky *et al*., 1999a; Harding *et al*. 2001; Drake *et al*. 2002; Means *et al*. 1999; Ni-meister *et al*., 2001). As with discrete return ALS, percentile statistics or profiles can be derived from return waveforms to describe vertical structure. Figure 4 (Lefsky *et al*., 1999a) illustrates the different structural metrics that can be derived from a full-waveform system.

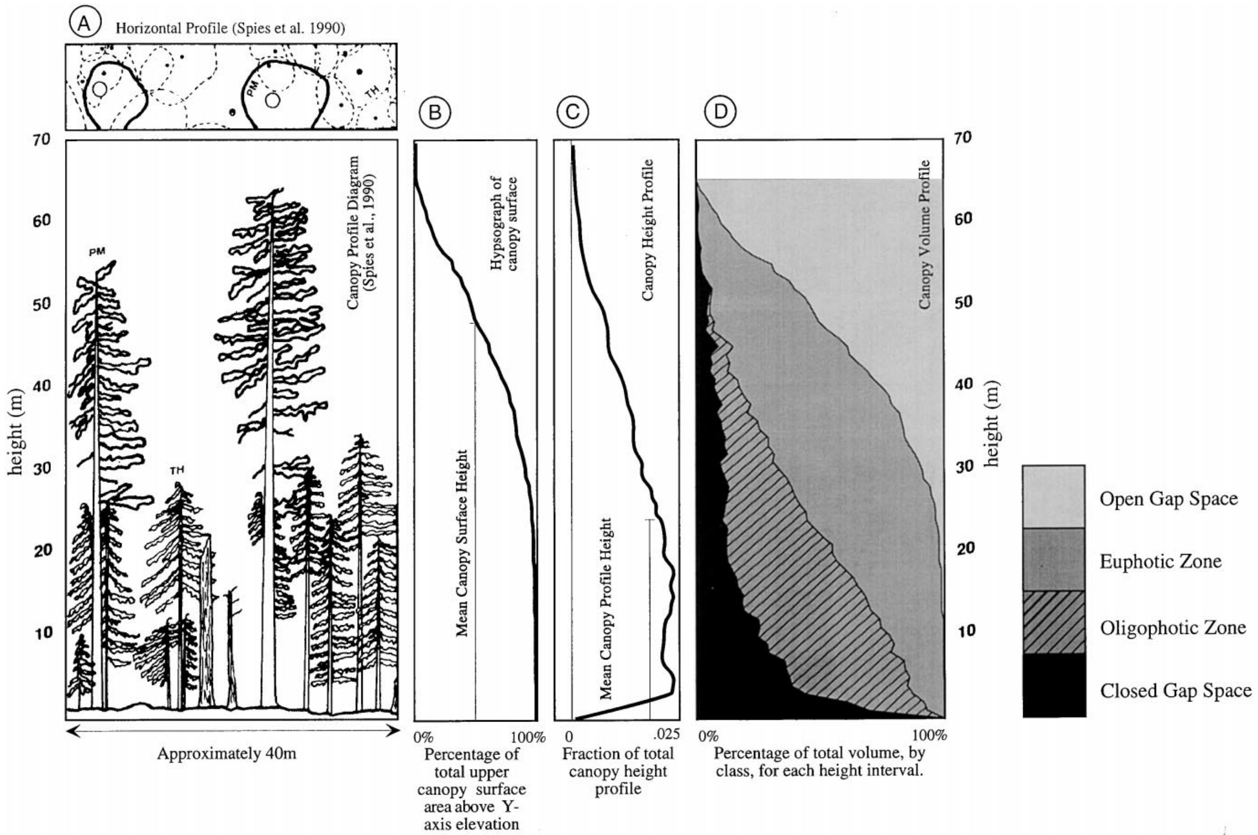

Figure 4. Characterising vertical structure with full-waveform LiDAR; (A) a schematic of a representative multi-layered canopy (Spies et al. 1990); (B) a canopy surface hypsograph, showing the vertical distribution of the upper canopy surface; (C) a canopy height profile, showing the relative vertical distribution of foliage, and; (D) a canopy volume profile, showing the vertical distribution of four classes of canopy structure (Lefsky et al., 1999a).

4.4.4 Australian context

There are a number of studies to determine vertical structure of Australian forests. For example, Crome and Moore (1992) applied the MacArthur and Horn (1969) method to estimate localised disturbance caused by logging and Fensham *et al*., (2002) utilised stereo aerial photography to distinguish different height strata. Laser scanning has been utilised in a number of studies to determine vertical structure, however analysis techniques have been varied. For example, Lovell *et al*. (2003) derived vertical profiles at a number of sites in NSW using small footprint ALS, highlighting its utility. Lee *et al*. (2004) described vertical structure at a site in QLD using a voxel approach. Lee and Lucas (2007) developed the HSCOI model to estimate the relative penetration of discrete-return ALS into the canopy therefore inferring structural complexity. Jupp *et al*. (2008) used a full-waveform terrestrial laser scanner to estimate vertical profile demonstrating the utility and accuracy of the Echidna instrument. Zhang *et al*. (2011) characterised Victorian cool temperate rainforest by statistically comparing stratified vertical profiles. Jaskierniak *et al*. (2011) fitted a number of distribution models to ALS derived bimodal vegetation profiles to characterise Mountain Ash stands. Finally, Miura and Jones (2010) used vertical structure and ALS return type to characterise Tasmanian dry sclerophyll forests.

4.5 Forest Cover and Leaf Area

4.5.1 Forest cover

4.5.1.1 Definition

Forest cover in the context of this review is a measure of the horizontal proportion of vegetation overlap of an area with a forest land use/land cover classification.

4.5.1.2 Characterisation

The proportion of forest cover provides a useful measure of the amount and distribution of foliage and allows for analysis at a number of spatial scales (White *et al.*, 2000). Canopy cover, a common descriptor of forest cover, is defined as the proportion of the forest floor covered by the vertical projection of tree crowns (Jennings *et al.*, 1999). Quantifying canopy cover is an integral component of determining forest from non-forest (UNFCCC, 2001; ABARES, 2012). Forest cover metrics provide significant insight to vegetation condition and are used for forest inventory assessment (Jennings *et al.*, 1999; Johansen and Phinn, 2006).
A wide range of cover and fractional variables exist which aim to characterise forest cover. Each cover metric aims to measure the proportion of vegetation overlap with reference to ground area. Cover is distinguishable from leaf area index (to be defined in section 4.5.2.2) as cover does not usually include the vertical proportion of vegetation overlap, thus restricting its range of values if given as a percentage from 0 to 100. Synonymous metrics have been grouped based on definition, not method of derivation. The key distinguishing factors between the outlined metrics in Table 6 are their applicability to a particular cover metric (McDonald *et al.*, 1990), whether in-crown gaps are included, and if the cover metric distinguishes Photosynthetically Absorbing Radiation in the canopy (PAR) elements from non-PAR canopy elements. Table 7 is a representative but not exhaustive list of cover metrics.

Foliage Projective Coverage (FPC)
Foliage Projective Cover (FPC) is 'a measure of the proportion of the ground area covered by foliage (or photosynthetic tissue) held vertically above it' (pp. 193, Specht and Morgan, 1981). FPC appears to be the same as Projective Foliage Cover (PFC) as cited in McDonald *et al.* (1990). FPC allows for gaps in tree crowns and irregularities in its outline, consequently giving a more realistic estimate of foliage cover in open canopies (Specht and Morgan, 1981). This authors used the term FPC to determine a 'climax' point or state of equilibrium for overstorey and understorey vegetation for given plant communities or species. The 'climax' point will depend on factors affecting vegetation growth such as climate, fire, disease and overgrazing to name a few. FPC provides a useful measure of total foliage in all but the most densely vegetated environments (Specht and Morgan, 1981). Therefore, FPC is suited to the rangelands in Australia containing Eucalyptus and Acacia trees and shrubs (Specht and Morgan, 1981). However, careful consideration must be

given to the vertical projection measurement technique with situations of vertical or near vertical leaves (McDonald *et al.*, 1990).

Canopy Cover

Canopy cover is an important environmental health indicator for riparian zones as it describes the amount and distribution of vegetation cover (Johansen and Phinn, 2006). It is also required for estimating forest stand statistics from remotely sensed images supporting forest inventory (Jennings *et al.*, 1999). Canopy cover is independent of tree height and the height of the measurement (Jennings *et al.*, 1999). Synonymous terms for canopy cover include canopy projective cover (Specht and Morgan, 1981), canopy percentage foliage cover (CPFC) (Johansen and Phinn, 2006), percentage canopy cover (PCC) (Johansen and Phinn, 2004), and crown cover (McDonald *et al.*, 1990; USDA, 1997).

Canopy cover is distinguishable from FPC. Firstly, because it includes non-photosynthetically active radiation (nPAR) absorbing canopy elements such as branches and stems, whereas FPC differentiates the PAR from nPAR elements. Secondly, canopy cover does not account for any gaps in the canopy or irregularities in the canopy outline, and therefore provides a less realistic measure of canopy coverage than FPC (Specht and Morgan, 1981). Lastly, FPC is able to distinguish different strata in the forest, whereas canopy cover cannot (McDonald *et al.*, 1990).

Canopy cover has been identified being able to exceed 100% in some studies, and limited to 100% in others. Cover is usually measured between 0 and 100 when quantified as a percentage. USDA (1997) stated canopy cover is as a measure being able to exceed 100%. However, in other studies canopy cover is quoted as being limited to 100% (Elzinga *et al.*, 1998; Jennings *et al.*, 1999). Canopy cover in USDA (1997) may exceed 100% if vegetation is split up into layers or stratum based on height above ground, counted separately and then combined. However, a meaningful result will not always be produced when quantified as a percentage if the layers are summed for a singular ground point and then averaged over a large area or number of points. Therefore, a clear distinction should be made if measuring canopy or vegetation layers as opposed to a general measure of vegetation cover.

Canopy Closure

'Canopy closure is the proportion of the sky hemisphere obscured by vegetation when viewed from a single point' (pp. 59, Jennings *et al.*, 1999). Canopy closure measurements will vary depending on the field of view (FOV) of the method employed and include both PAR and nPAR canopy elements (Jennings *et al.*, 1999). Canopy height and the height of the measurement viewing point influence canopy closure measurements (Jennings *et al.*, 1999). Canopy openness is the antonym of canopy closure (i.e. 1 - canopy closure = canopy openness) (Jennings *et al.*, 1999). Synonymous terms for canopy closure are canopy density (Jennings *et al.*, 1999) and plant projective cover (Arroyo *et al.*, 2010). Canopy closure is a more representative measure of light penetration through a canopy than canopy cover, as canopy cover treats tree crowns as opaque. Furthermore, canopy closure is a more robust measurement than canopy cover for foresters, as canopy closure is 'directly related to the light regime and microclimate and will therefore be linked to plant survival and growth at the point of measurement' (pp. 63, Jennings *et al.*, 1999).

Foliar Cover

Foliar cover is 'the percentage of ground covered by the vertical projection of the aerial portion of plants' (pp. 236, Anderson, 1986). Foliar cover is used in erosion models as it reflects variations in the density of the plant canopy associated with leaf and twig mortality (Pellant *et al.*, 2005). Foliar cover also reflects the changes in the size and number of individual plants in a defined area (Pellant *et al.*, 2005).

Two distinguishing factors between foliar cover and FPC are that FPC includes only PAR canopy elements and foliar cover can exceed 100% due to the inclusion of vegetation stratum. Foliar cover has been adopted as a measure of cover instead of canopy cover by USDA (1997) due to limitations of the canopy cover definition (Pellant *et al.*, 2005). Foliar cover, unlike canopy cover, does not include all spaces within the canopy regardless of whether there is vegetation due to treating tree crowns as opaque. This will result in a higher estimate of 'cover' and does not accurately reflect foliar cover (Pellant *et al.*, 2005).

Foliage Cover

Foliage cover as defined by McDonald *et al.* (1990, pp. 81) is 'the percentage of the sample site occupied by the vertical projection of foliage and branches (if woody)'. Foliage cover has many similarities with other key metrics listed in this review, however it is easier to distinguish based on differences which will be listed below.

Key differences between foliage cover and other cover metrics:

- The single distinguishing factor between FPC and foliage cover is that FPC includes only PAR canopy elements
- Foliage cover does not treat tree crowns as opaque and accounts for irregularities in the canopy outline. Therefore, foliage cover will never exceed canopy cover (McDonald *et al.*, 1990). However, McDonald *et al.* (1990) identified an allometric equation that allowed foliage cover to be converted from crown cover
- Foliage cover would be the same as canopy closure if it included a FOV in the measurement (i.e. a deviation off the vertical projection including an area of measurement)
- A difference between foliar cover and foliage cover is that foliar cover may exceed 100%
- Foliage cover is concerned with only woody vegetation elements, whereas other metrics do not make this distinction

Canopy Continuity

Canopy continuity is a measure of gaps in a canopy along a transect of a specified length and width (Dixon *et al.*, 2006). It is quantified as a percentage between 0 and 100 (Dixon *et al.*, 2006). The importance of canopy continuity by identifying gaps between crowns is measuring the connectedness of vegetation cover. Canopy continuity is a more approximate measurement of canopy cover.

Mean Crown Completeness

Mean crown completeness is defined as 'the proportion of the sky obliterated by tree crowns within a defined angle (or determined with a described instrument) from a single point' (pp. 63, Jennings *et al.*, 1999). The main purpose of mean crown completeness is to analyse canopies on an individual crown basis. Conversely, a defined field of view (FOV) could remain fixed for multiple measurements, which may incorporate multiple tree crowns depending on tree density. The main difference of mean crown completeness to canopy closure is that of scale, where measurements may target individual crowns rather than sections of the canopy consisting of multiple crowns. Furthermore, a distinction of mean crown completeness from other metrics is that mean crown completeness defines an angle of measurement or FOV from a single point, where this specification has been omitted by other definitions of cover metrics. Jennings *et al.* (1999) concluded that it is better to use the terms 'canopy cover' and 'canopy closure' (or openness) to differentiate between the two conceptually different variables instead of mean crown completeness.

Fractional Cover (fC)

Fractional cover is the proportion of an area that is covered by a specific land cover type (Scanlon *et al.*, 2002). Therefore, fC can be a flexible metric based on the fraction of the variable being described. Carson and Ripley (1997) described fC as the proportion of cover which pertains to the part of the vegetation canopy having no patches of bare soil between plants, where small holes in the vegetation cover and sun flecks at the surface were allowed. LAI and fC are closely related when fC values are less than 100% (Carlson and Ripley, 1997). fC can be measured at a range of scales which will determine the ability to measure gaps between and within tree crowns (White *et al.*, 2000). Different scales of measurement of the same area will theoretically produce different fC results. fC is also used for change detection in land cover and land use (Baret *et al.*, 2007).
Depending on the scale and method of measurement, fC will produce similar results to FPC if the fC variable includes only PAR elements of the canopy. The variation in results between FPC and fC will occur from the method of derivation. Canopy cover and closure methods are both included as measures of fC, which will produce biased fC results depending on the method chosen (White *et al.*, 2000; Baret *et al.*, 2007).

Crown Coverage

‘Crown coverage is the proportion of forest land area covered by tree crowns’ (Husch *et al.*, 1972). Crown coverage has been used predominantly to derive timber volume per unit area as it is an approximate measure of the density of trees (Husch *et al.*, 1972). Crown coverage as described by Husch *et al.* (1972) is ambiguous as both canopy closure and cover methods were specified, where some methods also include gaps in the crown and some do not. Therefore, depending on which method of derivation was chosen from Husch *et al.* (1972), crown coverage could be either canopy closure or canopy cover.

4.5.1.3 Methods and applications

Forest cover metrics can be derived *in situ* via visual assessment, vertical or projective sighting instruments, and digital photography to name a few (a full review can be found in Korhonen *et al.*, 2006). These methods are generally highly accurate but only characterise small areas when compared to large area forest cover mapping from remote sensing technologies. Table 6 presents applications of forest cover metrics utilised both within Australia and worldwide.

Table 6. Applications of forest cover metrics

Application	Context	Citation
Land Cover Classification	Global	(Friedl *et al.*, 2002; Scanlon *et al.*, 2002; Baret *et al.*, 2007)
	Australia	(Armston *et al.*, 2002; Guerschman *et al.*, 2009)
Vegetation Condition	Global	(Covington *et al.*, 1997; FAO, 2010a)
	Australia	(Johansen and Phinn, 2006; Barry *et al.*, 2008)
Forest Inventory	Global	(Husch *et al.*, 1972)
	Australia	(McDonald *et al.*, 1990; Scarth and Phinn, 2000; ABARES, 2012)
Ecological Modelling	Global	(Pellant *et al.*, 2005)
	Australia	(Setterfield *et al.*, 2005)

For large area applications of measuring and monitoring forest cover, remote sensing is the only feasible alternative (Foody and Curran, 1994). Remote sensing technologies such as optical imagery, LiDAR, and Synthetic Aperture Radar (SAR) have been utilised and are now widely accepted assessment tools for forest cover mapping (Coppin and Bauer, 1996; Wollersheim *et al.*, 2011; Wulder *et al.*, 2012). Forest cover and extent can be mapped through classification of vegetation often through vegetation indices derived from optical imagery (Lucas *et al.*, 2000); allometric equations and scaling factors from LiDAR (Lefsky *et al.*, 2002); reflectance, tone and texture of SAR (Knowlton and Hoffer, 1981); or a combination of remotely sensed data (Vaglio Laurin *et al.*, 2013). Current cover products for monitoring and mapping vegetation include fC derived from Landsat Thematic Mapper (Armston *et al.*, 2002) and MODIS (Guerschman *et al.*, 2009) for Australia (AusCover, 2012), and Land Cover globally from MODIS (Friedl *et al.*, 2002; USGS, 2012).

4.5.1.4 Australian context

The application of the cover metric will mainly determine which variation of cover is utilised. Within Australia, quantifying canopy cover is integral to distinguish forest from non-forest and for land managers at the state at territory government levels to fulfil their reporting obligations (Scarth and Phinn, 2000; DSE, 2007; ABARES, 2012). However, within Queensland FPC is widely used for cover reporting and monitoring purposes as it provides a more realistic measure of cover in rangelands containing Eucalyptus and Acacia trees and shrubs (Specht and Morgan, 1981). The ability of the states and territories to classify forest has improved with increasing availability and quality of remotely sensed data combined with advances in methodology (FAO, 2010b). For example, Australia’s forest extent was reported in the three State of Forest Reports in 1998, 2003 and 2008 to be 156.4 million hectares, 164.4 million hectares and 149.2 million hectares respectively. These variations were largely attributed to improvements in forest cover mapping rather than actual on-ground change (FAO, 2010b). Other uses of forest cover metrics within Australia include ecological assessments (Johansen and Phinn, 2004; Setterfield *et al.*, 2005) and input for forest typing (McDonald *et al.*, 1990).

Table 7. Forest cover metrics grouped based on their definition, outlining the metric name, whether or not photosynthetic and non-photosynthetic vegetation elements are distinguished, and whether gaps in the tree crowns are accounted. The cover classes “Closed or dense”, “Mid-dense”, “Sparse” and “Very sparse” correspond to a foliage cover of >70%, 30-70%, 10-30% and <10% respectively (McDonald *et al.*, 1990).

Metric Name	**PAR/nPAR**	**Crown Gaps**	**Cover Class Preference**	**Citation**
Foliage Projective Cover	PAR	Y	Sparse or very-sparse	(Specht and Morgan, 1981)
Projective Foliage Cover	PAR	Y	Sparse or very-sparse	(McDonald *et al.*, 1990)
Canopy Percentage Foliage Cover	Both	N	Sparse	(Johansen and Phinn, 2006)
Percentage Canopy Cover	Both	N	Sparse	(Johansen and Phinn, 2004)
Canopy Projective Cover	Both	N	Sparse	(Specht and Morgan, 1981)
Canopy Cover	Both	N	Sparse	(Jennings *et al.*, 1999)
Crown Cover	Both	N	Sparse	(McDonald *et al.*, 1990; USDA, 1997)
Canopy Closure	Both	Y	Mid-dense	(Jennings *et al.*, 1999)
Canopy Density	Both	Y	Mid-dense	(Jennings *et al.*, 1999)
Plant Projective Cover	Both	Y	Mid-dense	(Arroyo *et al.*, 2010)
Canopy Openness	Neither	Y	Mid-dense	(Jennings *et al.*, 1999)
Foliar Cover	Both	Y	Sparse	(USDA, 1997)
Foliage Cover	Both	Y	Sparse	(McDonald *et al.*, 1990)
Canopy Continuity	Both	Either	Sparse or very-sparse	(Dixon *et al.*, 2006)
Mean Crown Completeness	Both	Y	Sparse	(Jennings *et al.*, 1999)
Fractional Cover	Either	Y	Any	(Scanlon *et al.*, 2002)
Crown Coverage	Both	Either	Sparse to mid-dense	(Husch *et al.*, 1972)

4.5.2 Leaf area

4.5.2.1 Definition

Leaf area can be defined as the total surface area of the principal photosynthetic organ of vegetation. When quantified at scales lager than the individual leaf, it becomes an integral component of the structure and the functioning of vegetation making it a basic descriptor of vegetation condition (Asner *et al.*, 1998; Garrigues *et al.*, 2008a).

4.5.2.2 Characterisation

Leaf area can be characterised by the total amount of leaf tissue in the canopy per unit of ground area, which is commonly referred to as Leaf Area Index (LAI) (Watson, 1947; GTOS, 2009). Two main definitions have been suggested based on the shape of the leaves (Chen and Black, 1992). The first definition is for non-flat leaves, such as pine needles in coniferous canopies, where LAI is defined as half the total intercepting area per unit ground area (Chen and Black, 1992). The second definition is applicable to flat broad leaves, where LAI can be defined as the one-sided green leaf area per unit ground area (Myneni *et al.*, 1997). Within closed canopies LAI provides a more meaningful description of the amount of foliage present than canopy cover (Wulder and Franklin, 2003).

Multiple definitions and variations of LAI exist in the literature, mainly as a result of the method of derivation and the area of application. Different definitions have their strengths and weaknesses (Barclay, 1998; Asner *et al.*, 2003). Table 9 identifies ten variations and similar indexes to LAI. The metrics differ depending on the photosynthetic nature of the canopy element of interest, the broad- or needle-leaf forest canopy in which the definition is to be applied, and the method of derivation.

4.5.2.3 Methods and Applications

The LAI of a forest canopy can be measured both directly and indirectly. Direct measurement is limited to ground-based assessment and consists of destructive sampling, litter-fall collection, and point contact sampling to name a few. Indirect methods derive LAI from other variables such as the proportion of sky obscured from vegetation or estimated using allometric relationships from height and diameter at breast height (DBH) (Gower *et al.*, 1999). Direct methods are generally regarded as more accurate than indirect methods due to their independence of the influence of confounding factors such as leaf angle distribution, foliage clumping, variable sample size, and woody vegetation components (Jonckheere *et al.*, 2004; Weiss *et al.*, 2004). However, direct methods are inefficient and infeasible in some forest environments when compared with indirect methods due to their time-, labor-intensive, and destructive nature (Bréda, 2003; Jonckheere *et al.*, 2004).
Indirect methods provide a more efficient and cost-effective alternative to direct methods, which makes them more suitable for validation initiatives at larger scales (Jonckheere *et al.*, 2004). The more prominent indirect ground-based methods include optical instruments such as; cameras (with standard or fisheye lenses), the LAI-2200 Plant Canopy Analyser (Li-Cor Inc.), the Canopy Imager-110 (CI-110, CID Inc.), the DEMON (CSIRO, Canberra, Aus), and the TRAC instrument (Tracing Radiation and Architecture of Canopies, 3rd Wave Engineering) (Bréda, 2003; Jonckheere *et al.*, 2004; Keane *et al.*, 2005). More recently, methods use terrestrial laser scanning (TLS) to derive LAI indirectly (Lovell *et al.*, 2003). Presently there is no consensus among the scientific community for the best method to derive LAI at the ground scale (Gobron and Verstraete, 2009). The Committee on Earth Observing Satellites (CEOS) Working Group on Calibration and Validation (WGCV) Land Product Validation (LPV) sub-group is currently developing an international protocol for LAI to increase the quality and efficiency of global satellite validation (CEOS, 2012). This protocol aims to address the inconsistency among ground-based measurement and up-scaling techniques. Efforts such as this will assist to ameliorate the issue of inconsistency among definitions and methods to derive LAI.

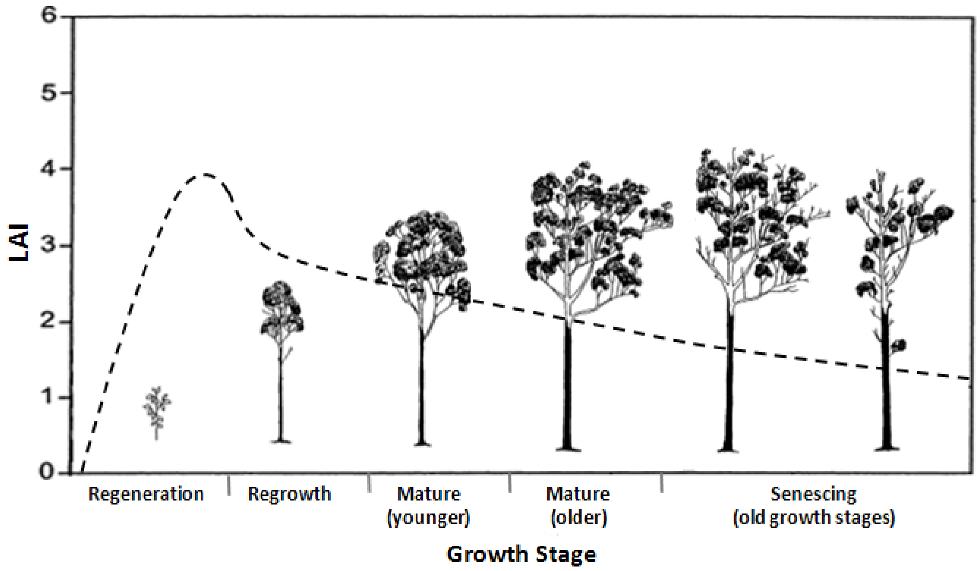

Figure 5. Forest growth stages based on Jacobs (1955) overlayed with an LAI curve of *Eucalyptus Regnans* (Vertessey *et al.*, 2001) – an approximation only

Table 8. Applications of LAI

Application	Context	Citation
Burn Severity Assessment	Global	(Bond-Lamberty *et al.*, 2002; Amiro *et al.*, 2006)
	Australia	(Boer *et al.*, 2008)
Evapotranspiration and Water Balance Assessment	Global	(Cleugh *et al.*, 2007; Leuning *et al.*, 2008)
	Australia	(Hatton *et al.*, 1995)
Climate and Growth Modelling	Global	(Cramer *et al.*, 1999; Sitch *et al.*, 2008; Stöckli *et al.*, 2008)
	Australia	(Almeida *et al.*, 2004; Stape *et al.*, 2004)

In contrast to direct methods, indirect methods are not constrained to measurement from the ground and can be derived at an airborne and space-borne level (Justice *et al.*, 2000; Zheng and Moskal, 2009; Armston *et al.*, 2012). Airborne and space-borne sensors provide the only viable means to monitor and model LAI from the regional to global scale. Active scanners such as LiDAR and RADAR emit their own energy source and provide more detailed structural information than passive imaging sensors (Zheng and Moskal, 2009). The structural information provided by active scanners can overcome limitations of passive sensors to model effective LAI. Active sensors at the air- and space-borne levels can assist with mixed pixels from passively sensed imagery (Chen *et al.*, 2004), and are not affected by cloud cover or vegetation saturation to the same degree. Thus, small footprint LiDAR is an attractive tool for validation of LAI at the regional scale (Zhao and Popescu, 2009; Armston *et al.*, 2012). However, global monitoring of LAI is only achievable from satellite imagery products such as MODIS LAI (Knyazikhin *et al.*, 1998)), CYCLOPES, and GLOBCARBON (Global Land Products for Carbon Model Assimilation) (Gobron and Verstraete, 2009). These products vary based on satellite sensor used, accuracy, spatial, and temporal extent (Garrigues *et al.*, 2008a).

Table 8 summarises applications of LAI such as studies of climate, ecosystem productivity, agrometeorology, biogeochemistry, hydrology, and ecology (Gobron, 1997; Garrigues *et al.*, 2008b).
LAI is recognised as an 'Essential Climate Variable' which supports '…research, modelling, analysis, and capacity-building activities…' requirements of the United Nations Framework Convention on Climate Change (UNFCCC) (pp. 1, GCOS, 2010). Running *et al.* (1986, pp. 273) identified LAI as 'the single variable both amenable to measurement by satellite and of greatest importance for quantifying energy and mass exchange by plant canopies over landscapes'. Furthermore, LAI directly influences the light penetration through to the understorey and thus is related to the succession stage of a forest (Lambers *et al.*, 1998). Figure 5 links the LAI of *Eucalyptus Regans* to the forest growth stage. The LAI rises to 4 at about 15 years and then

decreases to 1.3 at 235 years coinciding with the regeneration and senescing growth stages respectively (Jacobs, 1955; Vertessey, 2001).

4.5.2.4 Australian context

Within the Australian context LAI of forests has been used for a range of ecological and field modelling studies. To date, the majority of studies relied primarily on ground-based assessments of LAI. Specifically, it has been used to assess the burn severity of forest fires (Shugart and Noble, 1981; Boer *et al.*, 2008); water balance assessment and the impact on dryland salinity (Knight *et al.*, 2002); estimating stand transpiration (Hatton *et al.*, 1995); water stress and its impact on Net Primary Production (NPP) (Battaglia *et al.*, 1998); process-based growth modelling (Almeida *et al.*, 2004; Stape *et al.*, 2004); and an input in water catchment modelling (Vertessy *et al.*, 1998).

Table 9. LAI and or similar indexes. Specifically, it distinguishes the definitions based on; the photosynthetic nature of the canopy element of interest (PAR/nPAR), the canopy type in which it is to be used (Broadleaf/Coniferous), and the method of derivation.

Metric Name	**Photosynthetic Nature**	**Canopy Type**	**Methods**	**References**
Leaf Area Index	PAR only	B, C	Direct/Indirect	(Watson, 1947; Running *et al.*, 1986; Morisette *et al.*, 2006)
Effective Leaf Area Index	PAR only	B, C	Indirect	(Black *et al.*, 1991; Chen and Black, 1991; Chen *et al.*, 1997)
Vegetation Area Index, Plant Area Index	Both	B, C	Direct/Indirect	(Hutchison *et al.*, 1986; Chen *et al.*, 1991; Fassnacht *et al.*, 1994)
Effective Plant Area Index	Both	B, C	Indirect	(Chen *et al.*, 1991; CEOS, 2012)
Foliage (Surface) Area Index	PAR only	C	Indirect + conversion	(Fassnacht *et al.*, 1994; Jonckheere *et al.*, 2004)
Hemispherical Surface or Hemisurface Area Index	Either	C	Indirect + conversion	(Chen and Black, 1992; Fassnacht *et al.*, 1994; Chen *et al.*, 1997)
Wood Area Index, Woody Plant Area Index	nPAR only	B, C	Indirect (leaf-off conditions for deciduous forests)	(Neumann *et al.*, 1989; Bréda, 2003; Kalácska *et al.*, 2005)
Specific Leaf Area	Both (foliage only)	B, C	Direct (distinguishes between dry and green foliage)	(Gower *et al.*, 1999)
Shoot Area Index	PAR only	C	Direct/indirect	(Deblonde *et al.*, 1994; Chen and Cihlar, 1995)

Key:

Canopy types = (B) Broadleaf and (C) Coniferous forests
(n)PAR = (non-)Photosynthetically Active Radiation: part of the solar spectrum used in the photosynthetic process.

4.6 Tree species composition

4.6.1 Definition

Floristics can be analysed at different levels of detail; individual species, genera, and groups of genera that share similar characteristics. Forest classification is the procedure of grouping together entities that share similar characteristics (Delaney and Skidmore, 2001). The term *forest type* commonly refers to classification based on the dominant genus (Commonwealth of Australia 2012).

4.6.2 Characterisation

When mapping floristics, the aim is either to map the dominant species, determine species diversity/richness, or to map abundance/extent of specific key species. Studies on forest biodiversity can be grouped into those that directly map species, and those that map habitats and predict species distributions based on habitat properties and plant requirements (Nagendra 2001). Mapping of specific key species is done for identifying the abundance of endangered plants, species of special importance for the ecosystem, or alien species. In commercial forest management, it is used for assessing the abundance of merchantable tree species. Information about composition also plays an important role in mapping of forest structure and its further conversion into biomass and carbon estimates. When mapping structural attributes using remote sensing, relationships are often influenced by species composition and mapping accuracies can be improved from knowledge about species distributions (Anderson *et al.* 2008). Appropriate conversion factors (e.g. from stand volume to biomass) are also generally species dependent (Somogyi *et al.* 2007).

The species composition at the ground, middle, and upper canopy layers are all important for characterising the ecosystem. Field based inventories often collect species information in the different strata. However, remote sensing studies are almost exclusively limited to classifying the upper strata (Nagendra 2001). In most forest environments, the overstorey is simply too thick to enable mapping of sub-canopy species. Studies that have mapped understorey species in forests have either focused on a single species that grow in dense patches, e.g. bamboo (Linderman *et al.* 2004), or utilised statistical association with overstorey species (Joshi *et al.* 2006).

4.6.3 Methods and applications

Information about species composition has numerous applications (Table 10). Methodologies for discriminating types or species range from classifying individual tree crowns at the local level to estimating the dominant type or group of types at continental to global scales. Lucas *et al*. (2008) used aerial photography, CASI, and Hymap data to delineate and classify tree crowns in a 40 x 60 km area in Queensland. They classified the dominant tree species with an overall validation accuracy of 76%.

Table 10. Applications of typology/floristics.

Application	Reference
Biodiversity assessment	(Lindenmayer *et al.* 2000; Van Den Meersschaut and Vandekerkhove 2000; Clark *et al.* 2005)
Alien species mapping	(Ustin *et al.* 2002; Asner *et al.* 2008)
Wildlife habitat mapping	(Callaghan *et al.* 2011; Youngentob *et al.* 2011)
Disturbance	(Ross *et al.* 2002; Bhuyan *et al.* 2003)
Successional stages	(Franklin and Spies 1991; Woinarski *et al.* 2004)
Silvicultural planning	(Goodwin *et al.* 2005)

However, for large-scale classification projects, it is currently not economically feasible to procure such high spatial and spectral resolution datasets over very large areas. One alternative is to use aerial photography, as suggested by Tickle *et al*. (2006). But the lack of automated routines makes this approach reliant on aerial photograph interpretation (API). While API is a commonly used methodology, it is labour-intensive and dependent on the experience of the interpreter. Other disadvantages with aerial photography include the often limited spatial coverage that is dependent on the needs of the original project, and the large digital space needed to store high-resolution digital photographs (Morgan *et al.* 2010).

Species mapping generally rely on detecting the spectral differences between plants. With the increased use of LiDAR technologies, there have also been recent studies attempting to map species based on their structural differences. Dalponte *et al*. (2008) integrated hyperspectral and LIDAR data for classification of species in an Italian forest and found the addition of LIDAR derived heights useful for separating species with similar spectral characteristics but different mean heights. Other studies have relied solely on LiDAR to map tree species based on differences in crown shape and intensity features (Kim *et al.* 2009; Ørka *et al.* 2009). The latter examples require small footprint high density LiDAR data which seldom is available for operational inventories over larger areas.

Forest type mapping over larger areas often rely on low to medium scale multispectral products. For example, Xiao *et al.* (2002) used multi-temporal SPOT-4 VEGETATION data to map forest types in Northeastern China, and Helmer *et al.* (2012) used Landsat data to map tropical forest types in Trinidad and Tobago. Often mapping accuracies can be improved by combining satellite data with ancillary data products, such as climate and soil maps. Essentially, the ancillary data is used to model habitats, which are linked to the habitat requirements of different plants. Ruefenacht *et al*. (2008) used a variety of MODIS-based products, together with elevation, soil, and climate data, to map forest type and type group at 250m pixel resolution throughout the conterminous USA and Alaska. The high temporal resolution of MODIS data ensures adequate coverage and enables utilisation of phenological change as a predictor. They used classification trees to model 145 forest types and 28 type groups, with an overall accuracy of 50% and 69% respectively.

4.6.4 Australian context

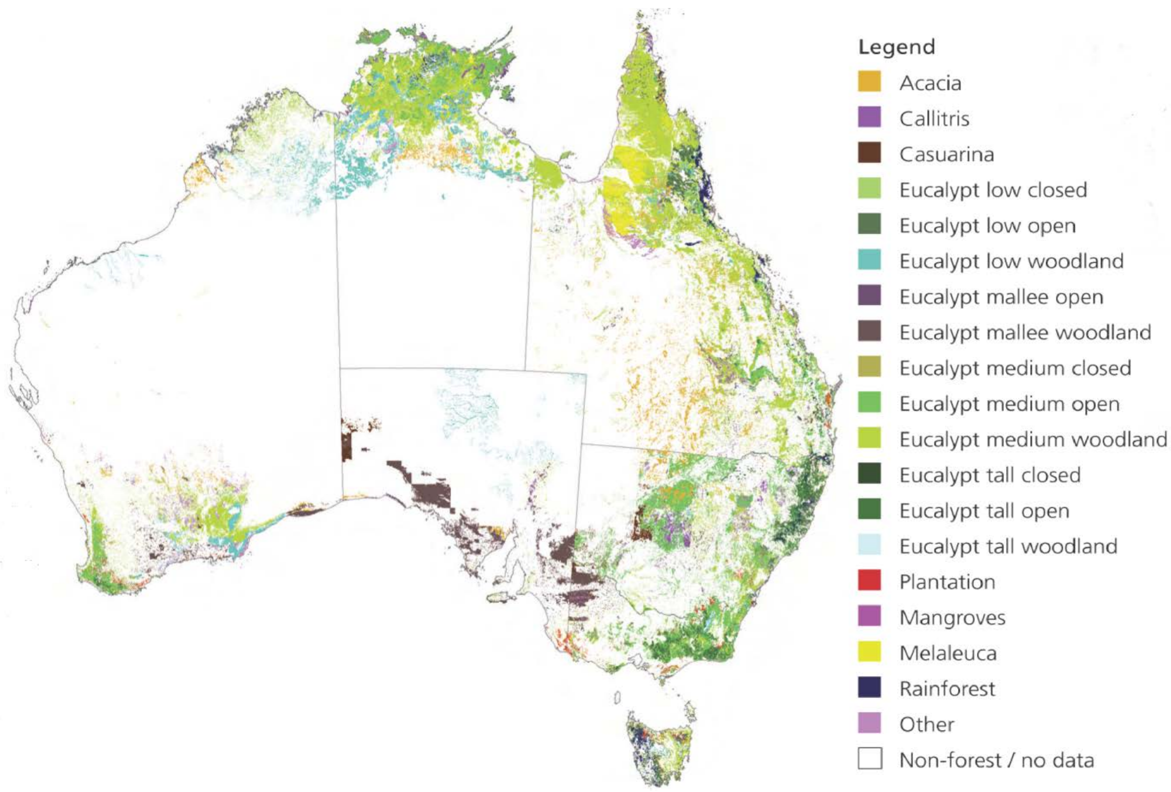

Figure 6. Map of Australian forest types (MPIGA, 2008).

The Australian national classification of forests is based on type (dominant genus) together with height and crown cover classes. Australia is heavily dominated by the eucalypt forest type (*Eucalyptus*, *Corymbia*, *Angophora* genera) covering 78% of the forested area. For national reporting purposes (Figure 6), forests are grouped into only 8 distinctive types: eucalypt (78%), acacia (7%), melaleuca (5%), rainforest (2%), casuarina (1%), mangrove (1%), callitris (2%), and "other" (3%). In addition, plantation forests are categorised separately into hardwood and softwood

(Montreal Process Implementation Group for Australia 2008). The national forest type classification is compiled by the National Forest Inventory (NFI) using data delivered by states and territories.

There is no consistent methodology behind data capture. Instead, each state and territory has established their own inventory framework catering for their specific needs. The implementation of common operational procedures, with focus on automatic processes, would likely lead to more cost-efficient data capture and processing at the state level. Moreover, it would lead to more consistent national products for reporting and for informing management and policy decisions.
For historical reasons, there is a range of different classification schemes used at the state level. These are often based on floristics, structure, and physiognomy (growth form), and designed either for wood production or conservation purposes (Sun *et al.* 1997). Delaney and Skidmore (2001) reviewed some of these, illustrated their use in a eucalypt forest, and evaluated their advantages and disadvantages. Some of the more widely used are listed below.

- *The Specht system* has been revised since its original presentation in 1970 (Specht, 1970). It classifies forests based on:
  (1) Structure of the dominant trees
  (2) Floristic composition among dominant trees
  (3) Floristic composition of the lower strata
- *Johnston and Lacey's classification* (Johnston and Lacey, 1984) classifies forests based on
  (1) Physiognomy, for example phenology, layering, foliage type, and leaf size and shape
  (2) Floristic compositions
  (3) Tree height and density (as expressions of disturbance and environmental conditions)
- *Braun-Blanquet's classification* is based on floristics; inter-species relationships, and relationships between species and the environment. A number of key (or diagnostic) species are identified and these are used to organise the community into a hierarchy.

Baur's Forest Types was intended for use in forest management but has also been adopted for conservation purposes. It describes the forest based on floristic composition, structure and habitat.

4.7 CWD

4.7.1 Definition

Coarse woody debris (CWD) consists of fallen trees, large branches and large woody fragments on the forest floor (Waddell, 2002; Woldendorp *et al*., 2004; Woldendorp and Keenan, 2005).

4.7.2 Characterisation

The CWD of a given area can be characterised with the total volume of fallen trees, large branches and large woody fragments on the forest floor (Victorian Government Department of Sustainability and Environment 2012). Woldendorp and Keenan (2005) also include coarse roots. Woldendorp *et al*. (2004) distinguish between standing dead trees (snags) and stumps and forest floor CWD; whereas Miura and Jones (2012) do not make such a distinction. Pesonen *et al*. (2008) defines CWD more broadly as downed trees that are not completely decayed. Hudak *et al*. (2012) define CWD in terms of length of time required for moisture retained in the wood to equilibrate with surrounding environments i.e. 1000-hour fuels (Fosberg *et al*., 1981); large CWD is often ignored in fire studies due to the length of time taken to burn (Woldendorp and Keenan 2005). Lindenmayer *et al*. (1999) characterise CWD as downed logs and woody debris with a diameter of >10 cm and a length >1 m, excluding logs of non-angiosperm origin. Applying an object based image analysis and LiDAR, Blanchard *et al*. (2011) characterised downed logs as between 0.25 – 1.5 m in width and between 5 – 25 m in length. Woldendorp and Keenan (2005) highlight the disparity in threshold used to characterise (1 cm – 20 cm) in Australia whilst Meggs (1996) suggest the need for consistency. Terms analogous with CWD include down logs, down wood, dead wood and logging residue (Waddell 2002).

Quantification of CWD volume is essential for carbon accounting, however is often overlooked Brown (2002). CWD plays an important role with regard to ecosystem health, for example, nutrient cycling (Pesonen *et al*. 2008), refuge and habitat for wildlife and providing sites for germination (Waddell, 2002). CWD has also proved useful for inferring successional stage Hudak *et al*. (2012). A review of CWD, quantity and spatial distribution within Australian forests is provided by Woldendorp and Keenan (2005).

4.7.3 Methods and applications

An assessment of CWD is included in the Victorian (Victorian Government Department of Sustainability and Environment 2012), Finnish (Pesonen *et al*., 2008) and US (Waddell, 2002) forest inventory programs, amongst others. Inventory techniques include line transects (Waddell, 2002), using a relascope (Ringvall *et al*., 2001) and fixed area assessments (Victorian Government Department of Sustainability and Environment 2012). Use of line transects captures more variability in CWD distribution when compared to other methods (Meggs, 1996). Woldendorp *et al*. (2004) suggest measurement of attributes including size, mass, density and orientation. Summaries of sampling techniques and rationale within Australia are provided by Woldendorp *et al*. (2004). Classification systems for degree of degradation include those that record decomposition (e.g. Lindenmayer *et al*., 1999) and classifications that also include size (Grove *et al*., 2011).

Although difficult to quantify from remote sensing (Pesonen *et al*., 2008), RS approaches have been presented and in particular utilising ALS. For example Aardt *et al*. (2011) regressed statistics from ALS derived last-of-many distribution functions with field measured CWD volumes.

4.7.4 Australian context

CWD assessment within Australia have utilised both traditional and RS techniques, a review is provided by Woldendorp and Keenan (2005). For example, Lindenmayer *et al*. (1999) used a 100 m transects to estimate CWD volumes in montane eucalypt forests, concluding that forest age class correlated well with diameter of CWD. Miura and Jones (2012) successfully inferred CWD volume by forest attribute characterisation using a vertical structure classification system.

4.8 Foliage chemical composition

4.8.1 Definition

In the context of this study, the foliage composition refers to the components existing in the leaf tissue of a canopy and their mean concentration in a stand when the assessment is at the stand level or over a specific unit area when the assessment is done at a larger scale. The foliage composition of a canopy has been found to be correlated with canopy health and biodiversity in Australian forest (Stone and Simpson, 2006; Asner *et al*., 2009). Moreover it can be used as input for models to predict net ecosystem productivity (Martin and Aber, 1997; Smith *et al.*, 2002). The interaction between vegetation and herbivores within the ecosystem has also been studied as function of the chemical composition of foliage and soils. According to Robertson (1991), leaf chemical composition is a major influence on between species differences in leaf consumption by insects. Herbivores feed from plants and are the proximal cause of mortality in eucalypt dieback, but as a feedback they play an important role as seed dispersal agents. All the above-mentioned demonstrates how critical the foliage chemistry is for the assessment of the ecosystem services (Martin and Aber, 1997).

4.8.2 Characterisation

Forest managers assess foliage composition by means of crown visual discolouration. That discolouration is based on the lack of pigmentation and later used together with defoliation to estimate canopy health. Foliage composition is then characterised by estimating leaf pigment content. That estimation can be done visually in the field or quantifying pigment concentration through laboratory analysis. Besides, the leaf spectral information is also function of the pigment concentration. The spectral reflectance of an individual leaf will vary as a function of three parameters: leaf pigment (type and concentration); leaf surface features; and leaf cell(s) (arrangement, physiological structure and water content). The relative contribution of each of these factors is wavelength dependent.

Individual leaf signatures are characterised by low reflectance in the visible and middle infrared wavelengths (dominated by pigment and water dependant absorption features) and high reflectance in the near infrared (dominated by cell structural features). Since the primary purpose of a leaf is photosynthesis, its first functional requirement is that photosynthetically active radiation is able to penetrate its surface. This is possible, since the top layer of leaf cells (the epidermis) is opaque and acts as a diffuse filter to photosynthetically active radiation (Knipling, 1970).

Inside the leaf, pigmentation is responsible for the majority of photosynthetically active radiation absorption. a and b chlorophyll, xanthophyll, the anthocyanins and the carotenoids are the main photosynthetic pigments. Their relative concentrations are dependent on plant-species, leaf-age, phenological stage and leaf-health, as well as site specific factors such as shading (Lloyd, 1989a; 1989b; 1989c; 1989d).

Leaf surface features such as hairs, spines, veins and cuticular wax all have an effect on leaf reflectance (Brakke *et al.*, 1989). Since these features vary from species to species, generalised effects are difficult to quantify. Canopy stratum leaves do however tend to possess more epidermal waxes than the leaves of the understorey vegetation. Their reflectance is therefore expected to be more specular.

There is little or no electro magnetic radiation absorption by leaf pigments in the near infrared wavelengths: Knipling (1970) and Gausman (1977) both estimate near infrared leaf absorption at 5%. Belward and Lambin (1990) offer an explanation for this low absorption, stating that the energy levels of near infrared are too low to drive the photochemical reactions of photosynthesis. The result is a region of high near infrared reflectance (0.75-1.3 um) that has been termed the near infrared plateau. These reflectance and transmission events result from interactions:

1. with the refractive index discontinuities along cell membrane interfaces, in the upper half of the leaf; and,
2. intercellular air spaces and hydrated cellulose cell walls of the spongy mesophyll, in the lower half of the leaf (Gausman, 1977; Lloyd, 1989a; 1989b; 1989c; 1989d).

The rates of transmittance and reflectance are approximately equal since the scattering processes, within the leaf, randomise the directions of radiation movement (Colwell, 1974). Other cell organelles cited as relevant to this process include the lysosomes, chloroplasts, stomata, nuclei, crystals, and cytoplasm. The intensity of the near infrared plateau in the spectral reflectance curve of a leaf will therefore increase as a function of the number, size, orientation and thickness of the spongy mesophyll cells (Gausman, 1977).

In the middle infrared wavelengths, reflectance is dominated by water absorption features. Liquid water possesses four absorption peaks, at 970, 1190, 1450 and 1940 nm. Leaf reflectance in the middle infrared wavelengths is therefore inversely related to total in vivo leaf water content (Gates, 1962; Gates and Tantraporn, 1952; Belward and Lambin, 1990;). Leaf surface water will increase the magnitude of these absorption features. At the leaf scale, pigment concentration, mesophyll cell orientation and leaf hydration are dependant not only on plant species but also on seasonal developmental stage. Gates and Tantraporn (1952) cite increases in chlorophyll concentration as leaves grow and mature, and decreases in chlorophyll concentration associated with leaf senescence (chlorosis). These leaf pigmentation changes may be extremely rapid (i.e. a few hours) (Daughtry and Biehl, 1985; Jacquemoud and Baret, 1990). During the initial stages of senescence, dehydration causes internal leaf volume to decline and the number of cell interfaces increase. This results in a rise in near infrared scattering and hence reflectance. As further dehydration occurs, cell walls split and re-orientate themselves; further increases in near infrared reflection may result. In the later senescent stages, cells collapse completely and form a series of horizontal layers. The general effect is that reflectance in the red wavelengths increases, whilst near infrared reflectance falls (Knipling, 1970; Rock, 1982; Rock *et al.*, 1988).

Canopy leaves are highly efficient in terms of photochemical production, but can dry out quickly at high temperatures. Waxy (water-retaining) derma are therefore common, as are recessed stomata. Despite these adaptations, leaf longevity is comparatively short and leaves are exchanged frequently to ensure optimum productivity. Plants in the understorey generally possess large thin leaves which provide a plentiful and easily penetrated light-absorbing surface. Chlorophyll content is high (to allow enhanced light absorption at low irradiance levels). As a result, such leaves are characterised by low photo-chemical conversion efficiencies. The photosynthetic pigments and pathways of shade species may become saturated at low (e.g. 100 μmol m-2 s-1) photosynthetically active radiation intensities, which equates to approximately 5% full sunlight. High proportions of chlorophyll-b (relative to chlorophyll-a) further enhance light absorbing capacity especially in the blue-green wavelengths, i.e. between the main red and blue absorbing bands of chlorophyll-a. Leaf angle orientation is likely to be at a variety of inclination angles in order to maximise absorption of photosynthetically active radiation that has already interacted with canopy vegetation (and been scattered).

4.8.3 Methods and applications

Usually, the assessment in the field is based on a visual estimation of the percentage of discoloured leaves in a crown. This assessment is made by a given operator, and in consequence, can be subjective. Alternatively, remote sensing of foliar chemistry has been recognised as an important element in producing large-scale, spatially explicit estimates of forest ecosystem function (Mooney *et al*., 1987; Steudler *et al*., 1989; Wofsy *et al*., 1993). Field sampling is costly and time consuming in the case of collecting leaves that later can be processed in the laboratory.

Nitrogen is a component of chlorophyll and is associated with important tree functions such as growth, leaf production, flower initiation, fruit set, and fruit development and quality. There are some indices specifically created for Nitrogen or pigment detection (Table 11). Many authors use the far red region to assess Chlorophyll content (examples can be found in Gates *et al*., 1965; Horler *et al*., 1983; Chappelle *et al*., 1992; Gitelson and Merzlyak, 1994; Datt, 1998; Curran *et al*., 1990; Vogelmann *et al*., 1993; Filella and Peñuelas, 1994), and others combine near-infrared and blue/green regions (as Peñuelas *et al*., 1994; Broge and Leblanc, 2000; Daughtry *et al*., 2000; Sims and Gamon, 2002; Haboudane *et al*., 2002), while the estimation of carotenoids is assessed using bands located in the visible (Gamon *et al*., 1992; Gitelson *et al*., 2002). It has been confirmed that the indices using multiple bands in their computations are more successfully applied to a wide range of species (Blackburn, 2007).

Table 11. List of remote sensing indices developed for N or pigment content estimation.

Index	**Acronym**	**Formula**	**Biophysiological parameter**	**Reference**
Normalized Difference Red Edge	NDRE	(R790-R720)/ (R790+R720)	Nitrogen	Barnes *et al*. (2000)
Normalized Difference Nitrogen Index	NDNI	[log (1/R1510)−log (1/R1680)]/[log (1/R1510) + log (1/R1680)]	Nitrogen	Fourty *et al*. (1996)
Nitrogen Reflectance Index	NRI		Nitrogen	
Normalized Difference Lignin Index	NDLI	[log (1/R1754)−log (1/R1680)]/[log (1/R1754) +log (1/R1680)]	Lignin content	Serrano *et al*. (2002)
Normalized Pigment Chlorophyll Index	NPCI	(R680-R430)/ (R680+R430)	Chlorophyll	Peñuelas *et al*. (1994)
Zarco-Tejada & Miller	ZTM	R750/R710	Chlorophyll	Zarco-Tejada *et al*. (2001)
Triangular Vegetation Index	TVI	0.5x[120x(R750-R550)-200x(R670-R550)]	Chlorophyll	Broge and Leblanc (2000)
Modified Simple Ratio	mSR	(R750-R445)/ (R705-R445)	Chlorophyll	Sims and Gamon (2002)
Red Edge	RE		Chlorophyll	
Transformed Chorophyll Reflectance Index	TCARI	3x[(R700-R670)-0.2x(R700-R550) x(R700/R670)]	Chlorophyll	Haboudane *et al*. (2002)
Modified Chlorophyll Reflectance Index	MCARI	[(R700-R670)-0.2x(R700-R550)]x (R700/R670)	Chlorophyll	Daughtry *et al*. (2000)
Structural Independent Pigment Index	SIPI	(NIR-R)/ (NIR-B)	Chlorophyll and carotenes	Peñuelas *et al*. (1995)
Carotenoid Reflectance Index	CRI	1/R510 - 1/R550	Carotenoids	Gitelson *et al*. (2002)
Photochemical Reflectance Index	PRI	(R570-R531)/ (R570+R531)	Xanthophyll DPS	Gamon *et al*. (1992)
Simple Ratio Pigment Index	SRPI	R430/R630	Pigment content	Peñuelas *et al*. (1995)

The indices developed at leaf scale are not always sensitive at canopy scale due to the confounding structural effects. The interaction of photons within the canopy layers depends on the leaf area index and the disposal of the leaves (leaf angle distribution) within the canopy (Norman *et al.,* 1985). Those structural effects modify the photon trajectory and the overall signal. Moreover, the structure is also affecting the proportional soil signal influence within the surface reflectance of a pixel.

Spectral ratios help normalizing for differences in illumination intensity resulting from overlapping canopy. Blackmer *et al.* in 1996 and later Osborne *et al.* (2004) concluded that the ratio between NIR and the green band was a good estimator of N content at the canopy scale. Gautam and Panigrahi (2007) used the same index combined with textural information extracted from infrared and red reflectance from imagery.

Some authors have found great utility in applying vegetation index ratios to overcome structural effects at the canopy scale. In this way, the effectiveness of an index developed at the leaf scale is not masked out by the structure of the vegetation and the soil background. For example, the case of the ratio between the Transformed Chlorophyll Absorption Reflectance Index (TCARI) divided by the Optimized Soil Adjusted Vegetation Index (OSAVI) developed by Haboudane *et al.* (2002) or the Normalized Difference Red Edge (NDRE) divided by the Normalized Difference Vegetation Index (NDVI) by Tilling *et al.,* (2006).

Alternatively to the use of vegetation indices to estimate chlorophyll content, the inversion of radiative transfer models can be used. At the top of the canopy, the interaction of the incoming radiation within the vegetation depends on the contribution of several components such as leaves, stems, soil, illumination and view properties of each canopy element, as well as on their number, area, orientation and position in space (Goel and Thompson, 2000; Koetz *et al*., 2005). Radiative transfer models simulate the interaction of the photons through the leaf and within the canopy architecture and give as result the top of canopy reflectance for a given conditions. At the leaf level, one of the inputs used to characterize the vegetation is the leaf chlorophyll content (Jacquemoud and Baret, 1990). Canopy reflectance extracted from multispectral imagery can be inverted with coupled leaf-canopy radiative transfer models to obtain leaf chlorophyll content (Jacquemoud *et al*. 1995). This methodology has the advantage of being applicable to different species, sensors and geometric conditions as it does not rely on empirical relationships obtained between vegetation indices and biophysical parameters. Leaf chlorophyll content has been derived from modeling inversion for grasslands (Darvishzadeh *et al*., 2008) and black spruce (Zarco-Tejada *et al*., 2004b).

There is not much documentation about remote sensing of nutrient deficiencies apart from nitrogen. Although N is consider the most important nutrient to monitor, other element deficiencies as Phosphorous can lead to lower shoot and root growth and eventually to a decrease in yield (Milton *et al*., 1991; Osborne *et al*., 2004). The biggest spectral differences due to leaf P concentration have been found in the 500-650 nm and near-infrared regions (Milton *et al*., 1991; Osborne *et al*., 2002; Yaryura *et al*., 2009). Phosphate deficient leaves have less inorganic phosphorous in the tissue water, lower photosynthetic and stomatal conductance rates and higher number of small cells per unit area (Jacob and Lawlor, 1991). The impact on the near-infrared can be attributed to the increase in the number of smaller cells in the palisade as leaf near-infrared reflectance is mainly responding to structure. The limited photosynthetic rate and the decrease of stomatal conductance are symptoms that are more affected by water or nitrogen stress. Changes in the green-red region can be due to a decrease of the pigment pool due to severe stress (Yaryura *et al*., 2009).

4.8.4 Australian context

The assessment of foliage chemistry in Australia has been done in the context of folivorous habitat mapping (Dury *et al.*, 2000), canopy health monitoring (Coops *et al.*, 2003; 2004; Barry *et al.*, 2008; 2011) or biodiversity assessment (Asner *et al.*, 2009). Barry *et al*. (2009) used radiative transfer modelling inversion to estimate chlorophyll content from eucalypt leaf spectra. Nevertheless, as existing models were developed based on European leaf reflectance and transmittance databases, difficulties arise when applying those models to leaves with a high content of oil and wax in the palisade tissue (Jacquemoud and Baret, 1990; Dawson *et al*., 1998).

There are a number of studies using remote sensing to assess canopy foliage composition in Australia. Most of the authors use specific vegetation indices (Coops *et al.*, 2003; 2004; Barry *et al.*, 2008; 2011; Asner *et al.*, 2009). Coops *et al*. (2003) used partial least squares (PLS) and multiple regression models (MLR) to estimate crown N content using high-spatial resolution satellite hyperspectral imagery.

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6 Appendix A

	Needs analysis for the assessment of the 28 biological indicators (Miles, 2002) as described by the Santiago Declaration at the sixth meeting of the Montreal Process Working Group (Montreal Process Working Group, 1995). The needs analysis assumes equal weight to each indicator. Metrics used to derive non-woody indicators are not included in this table and are labelled in the last column accordingly.	Tree/canopy height	Canopy coverage	Canopy/Understorey	Functional type	Flora species (Canopy / understorey)	Ground cover	Stem density	Basal area	CWD	Chlorophyll	Discolouration	Crown dieback	Non-woody metric
1	Extent of area by forest type relative to total forest area	x	x	x	x									
2	Extent of area by forest type and by age class or successional stage	x	x	x	x									
3	Extent of area by forest type in protected area categories	x	x	x	x									
4	Extent of areas by forest type in protected areas defined by age class or successional stage	x	x	x	x									x
5	Fragmentation of forest types	x	x	x	x									
6	The number of forest dependent species					x	x							x
7	The status (rare, threatened, endangered, or extinct) of forest dependent species at risk of not maintaining viable breeding populations, as determined by legislation or scientific assessment					x	x							x
8	Number of forest dependent species that occupy a small portion of their former range	x	x	x	x	x	x							x
9	Population levels of representative species from diverse habitats monitored across their range				x	x	x							x
10	Area of forest land and net area of forest land available for timber production	x	x	x	x			x	x					
11	Total growing stock of both merchantable and non-merchantable tree species on forestland available for timber production	x						x	x					
12	The area and growing stock of plantations of native and exotic species	x						x	x					
13	Annual removal of wood products compared to the volume determined to be sustainable	x						x	x					
14	Annual removal of non-timber forest products (e.g. fur bearers, berries, mushrooms, game), compared to the level determined to be sustainable													x
15	Area and percent of forest affected by processes or agents beyond the range of historic variation, e.g. by insects, disease, competition from exotic species, fire, storm, land clearance, permanent flooding, salinization, and domestic animals	x	x	x		x	x	x	x		x	x	x	
16	Area and percent of forest land subjected to levels of specific air pollutants (e.g. sulfates, nitrate, ozone) or ultra violet B that may cause negative impacts on the forest ecosystem													x
17	Area and percent of forest land with diminished biological components indicative of changes in fundamental ecological processes (e.g. soil, nutrient cycling, seed dispersion, pollination) and/or ecological continuity (monitoring of functionally important species such as nematodes, arboreal epiphytes, beetles, fungi, wasps, etc.)				x	x	x			x	x	x	x	x

18	Area and percent of forest land with significant soil erosion						x							x
19	Area and percent of forest land managed primarily for protective functions, e.g. watersheds, flood protection, riparian zones													x
20	Percent of stream kilometres in forested catchments in which stream flow and timing has significantly deviated from the historic range of variation													x
21	Area and percent of forest land with significantly diminished soil organic matter and/or changes in other soil chemical properties													x
22	Area and percent of forest land with significant compaction or change in soil physical properties resulting from human activities						x							x
23	Percent of water bodies in forest areas (e.g. stream kilometres, lake hectares) with significant variance of biological diversity from the historic range of variability													x
24	Percent of water bodies in forest areas (e.g. stream kilometres, lake hectares) with significant variation from the historic range of variability in pH, dissolved oxygen, levels of chemicals(electrical conductivity), sedimentation or temperature change													x
25	Area and percent of forest land experiencing an accumulation of persistent toxic substances													x
26	Total of forest ecosystem biomass and carbon pool, and if appropriate, by forest type, age class, and successional stages	x	x	x	x			x	x	x				
27	Contribution of forest ecosystems to the total global carbon budget, including absorption and release of carbon (standing biomass, coarse woody debris, peat and soil carbon)	x	x	x	x			x	x	x				
28	Contribution of forest products to the global carbon budget	x	x	x	x			x	x					x
	SCORE	14	11	11	12	6	8	8	8	3	2	2	2	17

7 Appendix B – Forest Attribute Survey

We constructed a short web-based survey and sent to people involved in land management. The objectives were to (1) better understand the needs of land managers, and (2) learn about additional forest attributes of importance for the potential user community. The survey was sent to 81 people of whom 32 responded. It was sent on May 4th, 2012, with the deadline set to May 31st. We used the SurveyMonkey web survey application (SurveyMonkey, Palo Alto, CA) for constructing the survey form and compiling the results. The survey was sent to professionals, directly or indirectly engaged with forest management, at a variety of agencies; state and federal government, private companies, and universities. Most were active in Australia and a few in New Zealand.

Table 1. Questions asked in the survey form.

#	Question	Type	Rationale
1	What type of agency do you work for?	Multiple choices. One answer allowed.	Learn about the perspective of the respondents.
2	What is your primary land management responsibility?	Multiple choices. One answer allowed.	Learn about the perspective of the respondents.
3	What data do you currently utilise for forest assessment and reporting?	Multiple choices. One answer per category.	Learn about current inventory methods.
4	What are the five most important forest metrics to capture using remote sensing from a forest management perspective?	Open-ended question.	Let the respondents brainstorm their own list of metrics.
5	Rank the importance of forest metrics from a forest management perspective.	Multiple choices. One answer per metric.	Let respondents rank our list of metrics.

The survey contained five questions (Table 1) about both forest attributes and the professional background of the respondents. The respondents were not forced to fill in answers to all parts of the survey form. In questions 3 and 5, respondents could tick some of the choices and leave others blank. Results for those questions are therefore presented in % of received answers. Question 4 is open-ended and generated a variety of answers. These were then grouped together with answers of similar meaning. The term *forest metric*, in questions 4 and 5, is used interchangeably with forest attribute. For question 5, we compiled a list of important forest attributes based on the literature and our own knowledge. Question 4 was intentionally placed on a page before question 5 so that the respondents did not see our list of forest metrics before compiling their own.
Of the 32 survey respondents, about half were employed by state agencies and most of these were engaged with either timber production or biodiversity/conservation (Table 2). The second largest employment type was research institute, which is dominated by the responsibility category of research.

Table 2. Employment type and primary responsibility of respondents.

Employment type / Primary responsibility	Federal agency	State agency	Research institute	Private sector	Total
Timber production	1	5	1	1	8
Biodiversity/ Conservation	1	7		1	9
Water	1				1
Fire management		2			2
Research	2	3	6	1	12
Total	5	17	7	3	32

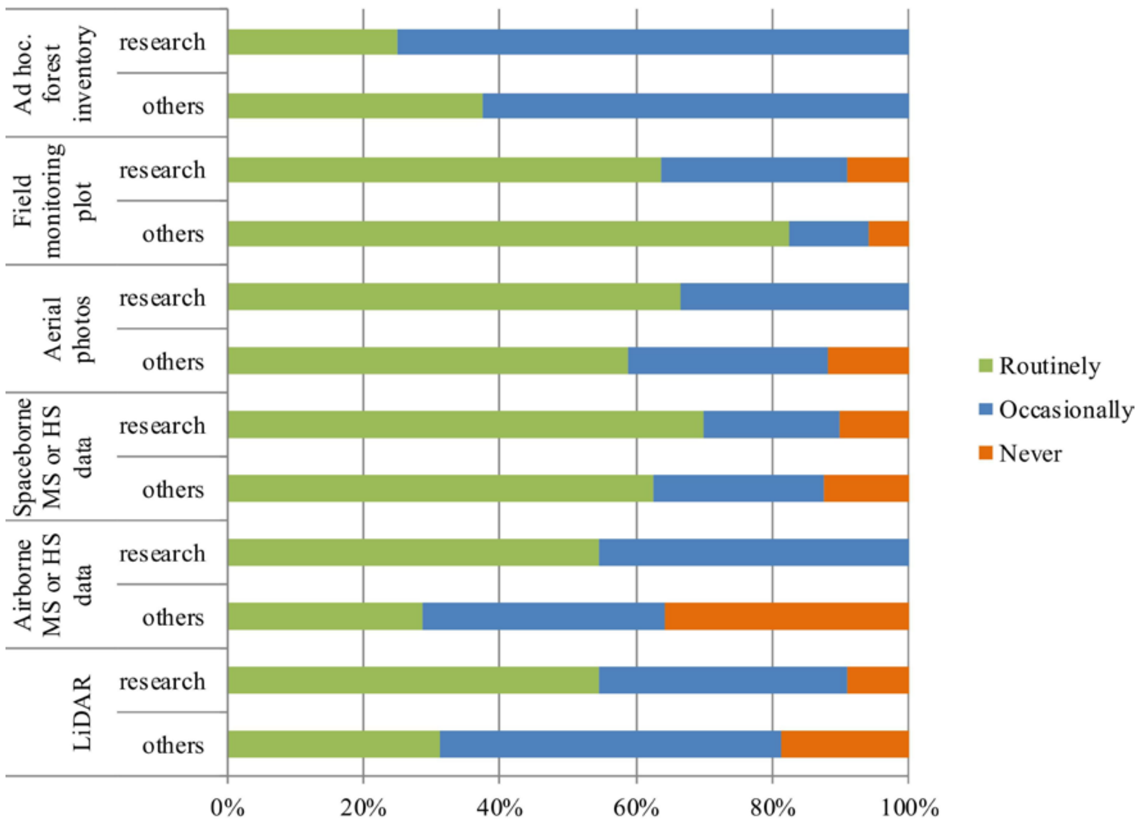

Figure 1. Currently used data sources for assessment and reporting. MS and HS stand for multispectral and hyperspectral.

Figure 1 shows which data is currently used in forest inventories. Respondents with "research" as primary responsibility are displayed as a separate group in order to highlight differences between current operational and research methodologies. All of the listed methodologies are widely used, either routinely or occasionally. The more routinely used methodologies are field monitoring plots (72% of respondents), followed by spaceborne multi- or hyperspectral imagery (65%), and aerial photography (62%).

The respondents list of important attributes (Table 3) reveals some clear trends. Tree height was considered the most important attribute, followed by condition and health, crown density, and species/type mapping.

Figure 2 contains results for the ranking of our list of forest attributes. The respondents assigned a level of importance to each attribute. Interpretation of the results depends on if focus is set on the *extremely important*, the *very important*, or the *important* level. With focus on the *important* level, attributes are ordered based on the percentage of votes at the *important* to *extremely important* levels. That results in aboveground biomass at the top, followed by change detection and canopy health. With a focus on the *very important*, change detection would be first, followed by canopy height and fire fuel loads. At the bottom, canopy water content, litter, and nutrient status, are the three least important according to either focus. Figure 3 compares the results for respondents divided into the three most common primary responsibility categories; biodiversity/conservation, timber production, and research. It only shows the percentage of votes at the *important* to *extremely important* levels.

The list of important forest attributes listed by the respondents (Table 3) is similar to the one we compiled (Figure 2). One attribute that was considered important, but was not on our list, is crown density. To summarise, the results show that the most important attributes are tree height, canopy health and condition, crown density, floristic composition, aboveground biomass, change detection, stem density, forest extent, and fire frequency/severity. Change detection is probably more accurately described as a methodology than a forest attribute. Nevertheless, its high ranking indicates a need for running monitoring programmes over longer time periods in order to detect changes.

Table 3. Important forest attributes listed by the respondents.

Forest attribute*	1st	2nd	3rd	4th	5th	Total

Tree height	6	2	4	2		14
Forest condition and health		4	3	2	2	11
Density of tree crowns (LAI or FPC)	3	4	1	2		10
Species/type mapping	3	1	2	3	1	10
Change detection	2	2	1	2	2	9
Forest cover extent	5	2	1			8
Fire frequency and severity	1	1	3	1	2	8
Timber volumes	2	1	2			5
Vertical foliage density profile	2	1	1		1	5
Biomass/carbon	1			3	1	5
Basal area	1	2		1		4
Productivity	1	1		1	1	4
Growth stage mapping	1				2	3
Canopy disturbance		1	1		1	3
Fragmentation			2	1		3
Forest diversity, mortality, stocking, crown shape, extent of understorey vegetation	-	-	-	-	-	2
Fire risk, DEM, water stress, nativeness of non-woody vegetation, drainage mapping, canopy connectivity, understorey LAI, main substructure type (small tree,shrub,grass), fuel load	-	-	-	-	-	1

*Attributes receiving one or two votes are aggregated; only the total number of votes is shown.

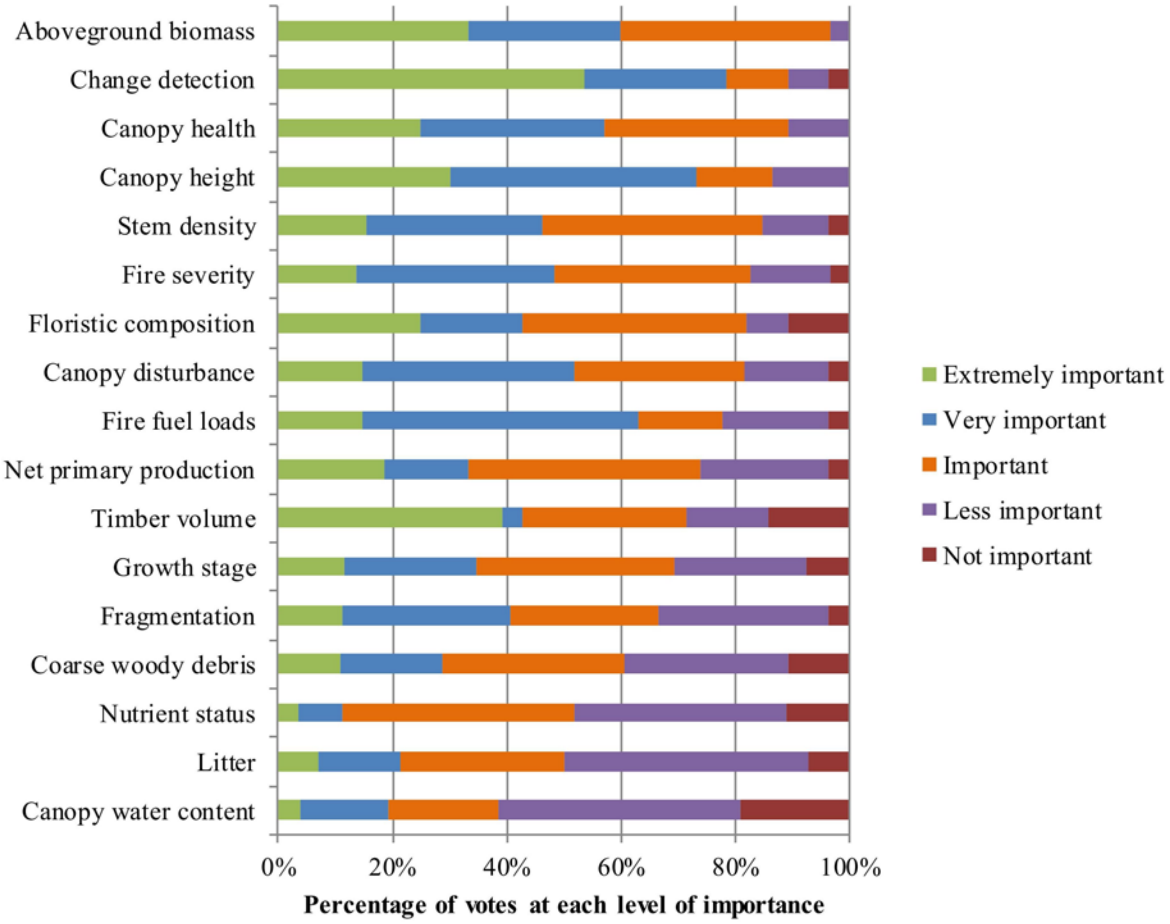

Figure 2. Ranking of forest attributes.

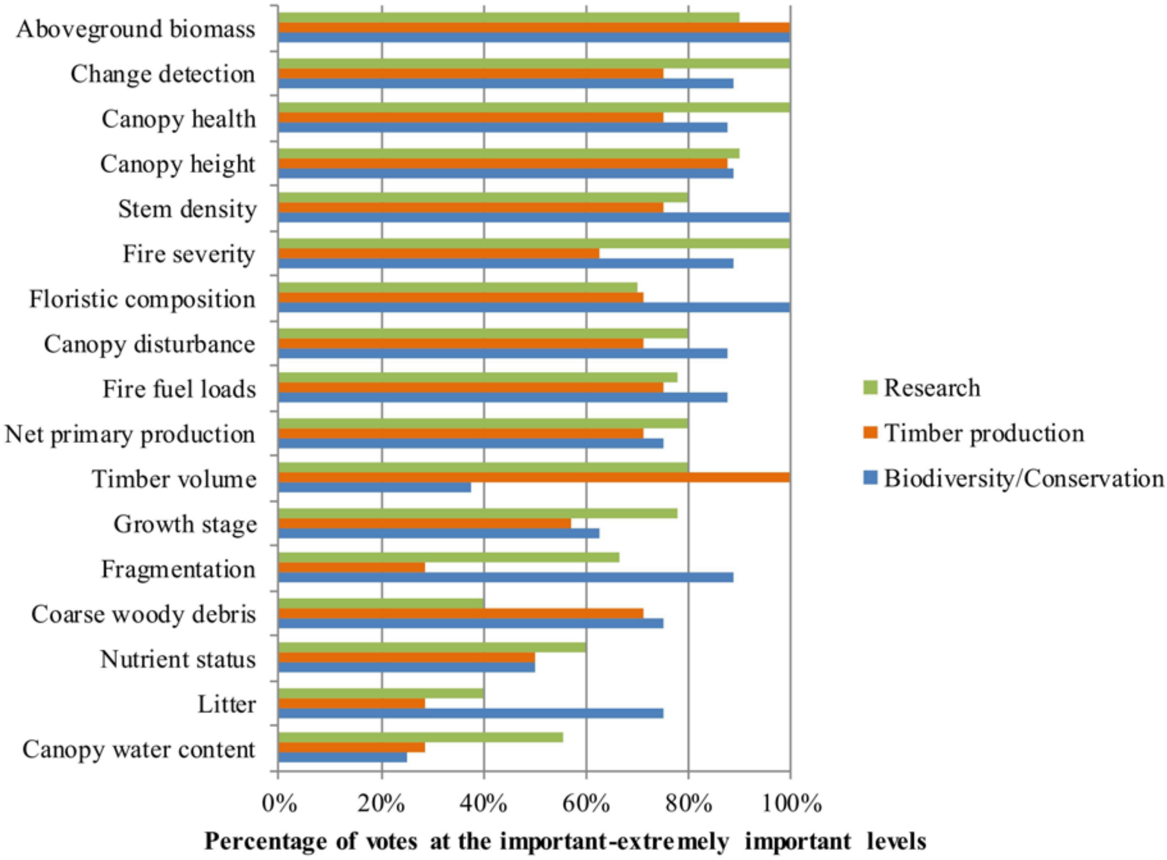

Figure 3. Comparison of attribute importance between respondent groups.