# Mapping glider habitat in dry eucalypt forests for Montreal Process indicator 1.1e: Fragmentation of forest types

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## Summary

Accurate habitat mapping is critical to landscape ecological studies such as required for developing and testing Montreal Process indicator 1.1e, fragmentation of forest types. This task poses a major challenge to remote sensing, especially in mixed-species, variable-age forests such as dry eucalypt forests of sub-tropical eastern Australia. In this paper, we apply an innovative approach that uses a small section of one-metre resolution airborne data to calibrate a moderate spatial resolution model (30 m resolution; scale 1:50 000) based on Landsat Thematic Mapper data to estimate canopy structural properties in St Marys State Forest, near Maryborough, south-eastern Queensland. The approach applies an image-processing model that assumes each image pixel is significantly larger than individual tree crowns and gaps to estimate crown-cover percentage, stem density and mean crown diameter. These parameters were classified into three discrete habitat classes to match the ecology of four exudivorous arboreal species (yellow-bellied glider *Petaurus australis*, sugar glider *P. breviceps*, squirrel glider *P. norfolcensis*, and feathertail glider *Acrobates pygmaeus*), and one folivorous arboreal marsupial, the greater glider *Petauroides volans*. These species were targeted due to the known ecological preference for old trees with hollows, and differences in their home range requirements.

The overall mapping accuracy, visually assessed against transects (n = 93) interpreted from a digital orthophoto and validated in the field, was 79% (KHAT statistic = 0.72). The KHAT statistic serves as an indicator of the extent that the percentage correct values of the error matrix are due to 'true' agreement verses 'chance' agreement. This means that we are able to reliably report on the effect of habitat loss on target species, especially those with a large home range size (e.g. yellow-bellied glider). However, the classified habitat map failed to accurately capture the spatial patterning (e.g. patch size and shape) of stands with a trace or sub-dominance of senescent trees. This outcome makes the reporting of the effects of habitat fragmentation more problematic, especially for species with a small home range size (e.g. feathertail glider). With further model refinement and validation, however, this moderate-resolution approach offers an important, cost effective advancement in mapping the age of dry eucalypt forests in the region.

*Keywords*: wildlife, ecology, surveys, spatial distribution, forest, habitats, prediction, models, fragmentation, gliders

## Introduction

Criteria and indicators are increasingly necessary to provide a common framework for assessing and evaluating progress towards ecologically sustainable forest management at the regional and national level (Brand 1997; Bunnell 1997; Raison *et al*. 2001). As a signatory to the Montreal Process (Anon. 1995), Australia has national and international obligations to report on regional indicators of forest sustainability (MIG 1998). Montreal Process Indicator 1.1e, fragmentation of forest types, is designed to assess and monitor biological diversity in Australia's forest landscapes (MIG 1998), where loss and fragmentation of old forests and clearing of private forests are major issues (e.g. Loyn 1985, 1998; Saunders et al. 1991; Lindenmayer *et al*. 1999; Ludwig *et al*. 2001). Within production forests, loss and fragmentation of old forest has important consequences for forest fauna populations with an ecological preference for hollows (e.g. Lindenmayer et al. 1990; Eyre and Smith 1997; Gibbons and Lindenmayer 1997). Typically, these pressures occur at fine spatial scales such as forest stands (1-10 ha), but cumulatively impact on the structure and function of larger forest landscapes at scales of 10s-100s $km^2$ (Burris and Canter 1997; McAlpine 1999).

Accurate mapping is a key issue in developing reliable indicators of habitat loss and fragmentation, especially in these structurally complex forest landscapes (Haines-Young and Chopping 1996; Hargis *et al*. 1998; Tickle *et al*. 1998a; Wallace and Campbell 1998; Loyn and McAlpine 2001). This is important for two reasons.

First, habitat mapping must match the ecology of the target species, as species have different responses to habitat loss and fragmentation according to their life history attributes such as scales of movement (O'Neill *et al*. 1988a; With and Crist 1995; Pearson *et al*. 1996; Withers and Meentemeyer 1999). For example, the greater glider (*Petauroides volans*), an arboreal folivore, differs in home range size, social organisation and diet compared to the yellow-bellied glider (*Petaurus australis*), an arboreal exudivore (Smith and Hume 1984; Goldingay and Kavanagh 1991). These life history differences need to be taken into consideration in landscape mapping and subsequent analysis of landscape-scale influences on species distribution and abundance. It is imperative, therefore, that habitat mapping be consistent with a species' habitat preferences and scales of movement.

Second, once the first prerequisite has been met, the resulting remotely sensed landscape structure must accurately capture both the relative proportion of each habitat type (landscape composition), and its spatial configuration (Hess 1994). Remote sensors such as Landsat Thematic Mapper ™ are being used to map forest cover with increasing success (e.g. Ehrlich *et al*. 1997; Danaher *et al*. 1998; Goulevitch *et al*. 1999; Ma *et al*. 2001; Oetter *et al*. 2001). However, discriminating among age structural types is difficult (e.g. Preston and Moore 2000; Lefsky *et al*. 2001). This is particularly important for assessing within-forest fragmentation, where the accurate mapping of fine-scale variations in forest age structure over the whole landscape is fundamental to developing reliable fragmentation indicators. Aerial Photograph Interpretation (API) has traditionally been used for this task. API is subjective, however, and is not able to accurately capture fine-scale variation in stand age necessary for ecological studies (Scarth *et al*. 2001). High-resolution Digital Multi-Spectral Video data has proved moderately successful in predicting the age of temperate eucalypt forests with even-aged stands and for predicting eucalypt habitat complexity for wildlife management (Coops and Catling 1997; Coops *et al*. 1998; Catling and Coops 1999; Preston and Moore 2000). However, these methods have been less successful in sub-tropical dry eucalypt forests such as those of south-eastern Queensland, which are a heterogenous mix of trees species of different height, crown morphology and spacing. This limitation poses a major challenge in developing Montreal Process indicator 1.1e for these dry eucalypt forests. This problem can be overcome by the development of digital remote sensing techniques, which accurately capture within-stand-scale variations (<1 ha) in forest age structure over whole forest landscapes (e.g. Imhoff 1997; Lefsky *et al*. 2001).

In this paper, we outline methods that apply a modified Geometric-Optical (GO) model (Scarth and Phinn 2000; Scarth *et al*. 2001) to Landsat Thematic data to map the age structure of a dry eucalypt forest near Maryborough, south-eastern Queensland. The study is one of three case study areas for the development and testing of Montreal Process indicator 1.1e in Australia (Lindenmayer *et al*. 2000). The accuracy of classified age structure classes derived from GO-model outputs is visually assessed against the structure observable in a high-resolution digital orthophoto. The age classes are then combined with forest floristic data derived from a forest inventory spatial database to provide species-sensitive habitat classes essential for reliable indicator development. Age classes were selected to match the ecology of four exudivorous species including the yellow-bellied glider, the sugar glider *P. breviceps*, the squirrel glider *P. norfolcensis*, and the feathertail glider *Acrobates pygmaeus*; and one folivorous arboreal marsupial, the greater glider. These species were targeted due to the known ecological preference for old trees with hollows, and the differences in their home range requirements. Forest floristic associations also need to be included in the habitat mapping, as the four exudivorous species prefer spotted gum/ironbark floristic associations over stringybark/bloodwood associations (Smith and Hume 1984; Eyre and Smith 1997). Spotted gum/ironbark associations provide an important nectar resource, especially over the winter months, while over-mature and senescent gum-barked tree species provide a sap resource for exudivorous species.

## Methods

### Study area

The study area (400 km²) is located approximately 30 km south-west of Maryborough in south-eastern Queensland (25º39'S; 152º26'E), and includes St Marys State Forest (SF) and surrounding partially cleared agricultural and grazing lands (Fig. 1). St Marys SF (17 400 ha) is a continuous expanse of dry eucalypt forest (Eyre and Smith 1997), while the surrounding landscapes are a mosaic of grazing, cropping and forest landscape elements. Site productivity within St Marys varies from low on the sandstone ridges to moderate-high along the alluvial drainage lines. Dominant species include: spotted gum (*Corymbia citriodora*), brown bloodwood (*C. intermedia*), yellow bloodwood (*C. trachyphloia*), grey ironbark (*Eucalyptus siderophloia*), broad-leaved iron bark (*E. fibrosa*), narrow-leaved ironbark (*E. crebra*), Queensland blue gum (*E. tereticornis*), smoothed-barked apple (*Angophora leiocarpa*) and yellow stringybark (*E. acmenoides).* These species form broad forest types, with the main communities being

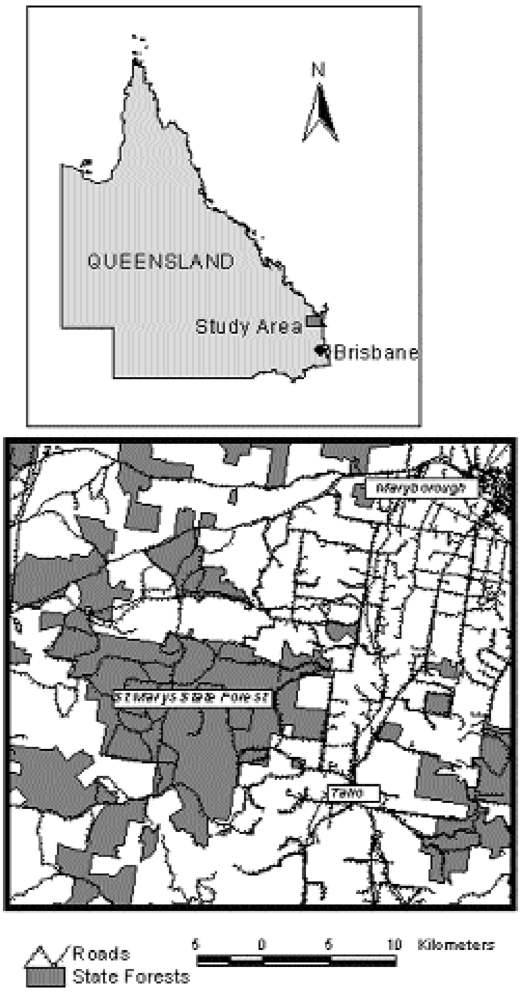


**Figure 1.** Location of study area focusing on St Marys State Forest and surrounding partially cleared landscapes

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*C. citriodora- E. siderophloia*, *C. citriodora- E. fibrosa*, *C. citriodora- E. siderophloia*, and *C. intermedia- C. trachyphloia* (Eyre and Smith 1997). Stand age structure has been substantially modified by selective logging disturbance, which has created a regrowth-dominant forest interspersed with scattered stands of over-mature and senescent trees, many unsuitable for logging (McAlpine 1999).

## Geometric-optical model algorithm

An innovative approach integrating high- and moderate-spatial resolution airborne and satellite image data sets was developed to estimate canopy structural properties in St Marys State Forest (for full details see Scarth and Phinn 2000; Scarth *et al*. 2001). Scarth and Phinn (2000) successfully implemented the model in a wet-dry eucalypt forest near Killarney, south-eastern Queensland, by combining high-spatial resolution airborne image data and field survey data to optimise the model in test sites before applying to the whole image. The approach used an image processing model that assumes each image pixel is significantly larger than individual tree crowns and gaps, hence, the recorded reflectance value in each pixel is an area-weighted combination of reflectance from sunlit canopy, sunlit background, shaded canopy and shaded background components (Fig. 2). If assumptions are made concerning the geometry of tree crowns and their spatial distribution, a non-linear least squares spectral unmixing approach can be applied to estimate the areal fraction of each pixel occupied by sunlit canopy, sunlit background, shaded canopy and shaded background components. A geometric-optical model that defines how canopy structural parameters control individual pixel reflectance can then be inverted to derive individual-pixel-based estimates of crown-cover percentage, stem density and mean crown diameter. Initial development and testing of this geometric-optical modelling was undertaken in coniferous forests by Li and Strahler (1985) and Li and Strahler (1992), and was extended to incorporate Boolean models for random sets in a three-dimensional space by Strahler and Jupp (1990). Subsequent work using geometrical-optical models is well summarised in Wanner *et al.* (1995). Jupp and Walker (1997) further discuss the benefits of geometrical-optical modelling in detecting forest structural change for management purposes.

In this project, a similar approach was applied, and is described in detail by Scarth *et al*. (2001). A discrete sequence of processing operations was applied to the Landsat TM and DMSV images (Fig. 3) to derive estimates of forest structural parameters. This sequence involved initial de-noising of the Landsat TM image using a maximum noise fraction transform (Green *et al.* 1988), followed by an analysis of the scene to find and extract the reflectance of each pure cover type using an autonomous end-member determination method based on Winter *et al*. (1998). These pure reflectance spectra are termed image end members, with the analysis of spectral mixtures often termed ‘end member analysis’ (Jupp and Walker 1997). These image end members were then optimised using a process of iterative calibration that used both field-assessed crown cover projection data at selected points and the semivariance of the DMSV image as an estimate of relative canopy size. The objective was to minimise the error between the model and field crown cover projection estimates. To achieve this, we used Shor’s r-algorithm (Shor 1985) to find a local minimum of the non-linear function that computes the crown size and cover from the end members, and therefore reduce the error between

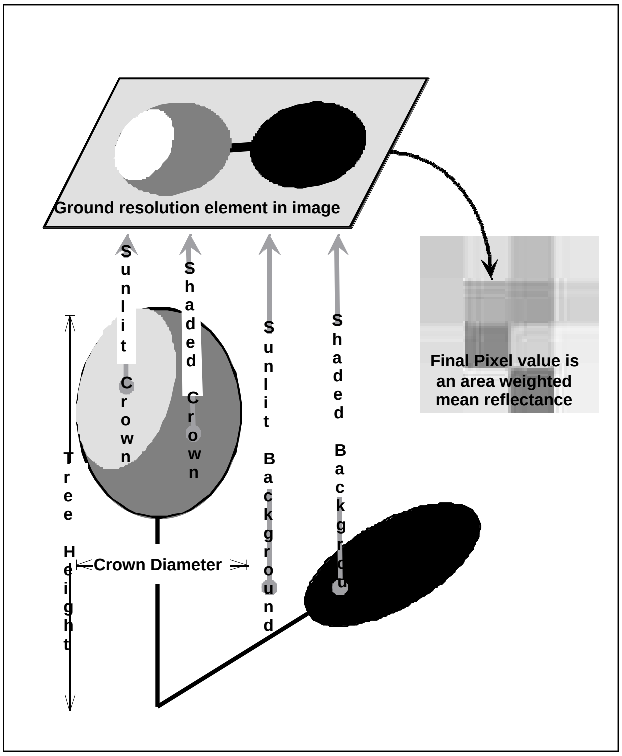


**Figure 2.** Conceptual schema of the Li-Strahler Geometric-Optical model, indicating the scene components contributing to the measured response in each ground resolution element

the model output and field determined crown cover projection. This produced a new set of refined image end members that were then used in conjunction with a fast non-negative least squares unmixing algorithm (Bro and De Jong 1997) to transform the TM data into four fraction images of sunlit background, shaded background, sunlit canopy and shaded canopy along with an estimate of the error where the four end members failed to represent the image data. The fraction images, along with the field-determined model parameters, were input into a geometric optical model that determined a ‘treeness’ index, equivalent to the number of trees per pixel multiplied by the square of the crown radii. Pixels where topographic shadow prevented calculation were given a value of zero. The local variance of the ‘treeness’ index within an 11x11 pixel moving window was then calculated and used, as outlined in Scarth and Phinn (2000), to determine the projected crown cover, the mean crown diameter in metres, the number of trees per pixel and the skewness of the crown diameter values as an estimate of successional stage.

## Landscape classification

An unsupervised classification (ISODATA) routine (ERDAS Imagine 8.3.1 Software, ERDAS 1998) was applied to the crown cover, stem density and mean crown size GO model-derived data to produce ten structural classes. The ISODATA classification algorithm groups data into classes as required so that the within-cluster sum of squares is minimized. This algorithm finds a ‘local’optimum in which no movement of an observation from one cluster to another will reduce the within-cluster sum of squares. Since the ISODATA algorithm calculates the cluster configuration for a fixed number of clusters, the operator must decide on an appropriate number of classes before

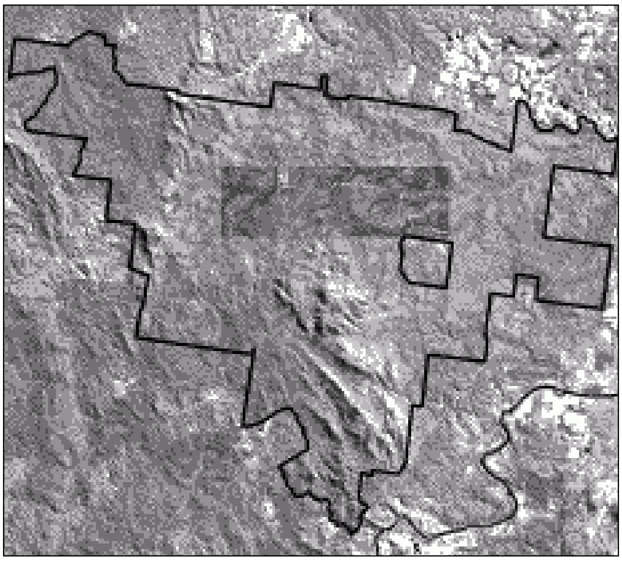

**Figure 3.** Reflected near-infrared radiation from the St Marys State Forest recorded by the Landsat Thematic Mapper instrument overlayed with one-metre resolution Digital MultiSpectral Video (DSMV) and digital orthophoto data

running the algorithm. One criterion for deciding on the optimal number of classes is to locate the point where the percent of variation (given as the within sum of squares for the number of clusters as a percentage of the within sum of squares with no clustering) fails to decrease dramatically. Figure 4 gives the results of this analysis, which shows that ten classes would appear to be optimal, with a greater number of classes giving a limited decrease in the percentage of variation and resulting in greater operator effort in interpreting the result. The mean values of the structural classes were plotted and interpreted, and subsequently labelled and merged into three broad structural classes (Fig. 5). These classes are aggregations of ecological maturity classes used for API mapping of forest age structure in south-eastern Queensland (DNR 1998).

**Class 1: Cleared and partially cleared habitats.** Grazing and agricultural lands, and disturbed forest stands with less than 30% crown cover. These habitats have an open structure, often with scattered trees in a grazing or agricultural matrix, and represent largely hostile habitat for arboreal marsupials.

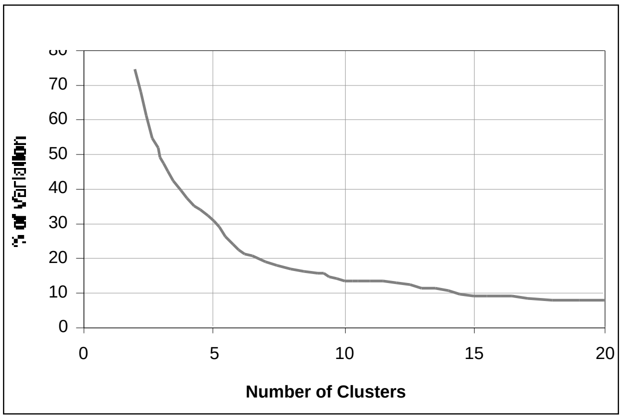


**Figure 4.** The percent of variation for various numbers of ISODATA-derived clusters used to determine the optimal number of final classes

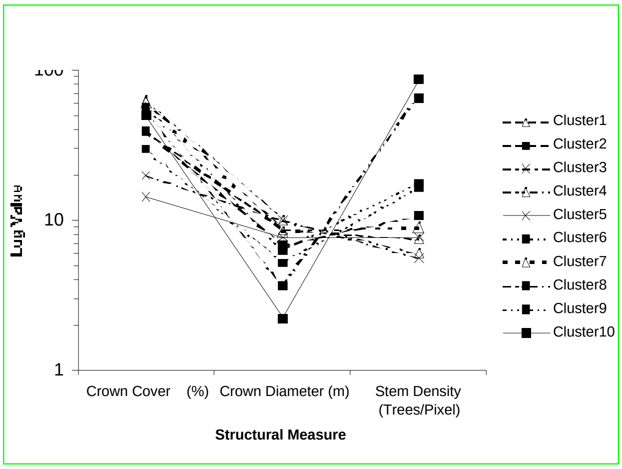


**Figure 5.** Line graph of means value of ISODATA clusters for: crown cover (%), crown diameter (m) and stem density (trees/pixel). Clusters 1, 4 and 7 were categorised as Class 3 habitats based on high mean crown diameter values. Clusters 2, 6, 8, 9 and 10 were grouped as Class 2 habitats based on low mean crown diameter and high stem density values. Clusters 3 and 5 were grouped as Class 1 habitat based on low mean crown cover values.

**Class 2: Regrowth-Mature habitats.** Dominated by pole, regenerating and/or early mature trees with small crowns, relatively uniform in shape, and a tight clustering of high density stems indicating relatively recent, intense selective logging disturbance. This habitat class has dense tree cover, but old trees providing nesting dens for all species (Smith and Hume 1984) and sap trees for exudivorous species (Eyre and Smith 1997) are largely absent. However, *Acacia* spp. in the variable understorey provide a food source for the greater glider, an arboreal folivore (Kehl and Borsboom 1984; Eyre unpublished data).

**Class 3: Trace-subdominant.** Heterogeneous mix of regrowth, mature and senescing trees with at least one percent of over-mature and late-mature trees per unit area (hectare) (DNR 1998). Stems are less dense while crown morphology exhibits a coarse, but solid, grain compared to Class 2. In dry eucalypt forests such as St Marys, the upper canopy is generally closed with either a dense or sparse understorey compared to the more variable canopy cover of disturbed regrowth forests (Class 2). Class 3 habitats have low to moderate proportions of over-mature and senescent trees with hollows.

The structural parameters (derived from the GO model) of the grouped habitat classes are summarised in Table 1. The high number of stems in Class 2 (mean 272 ± 165) is indicative of the high proportion of small size stems (< 40 cm dbh) in overstocked regrowth stands that dominate St Marys SF. For crown cover percent, Class 2 (mean 41.3 ± 17.3) and Class 3 (mean 38.7 ± 18.3) also showed a strong separation, while there was a significant difference between Class 1 (mean 19.6 ± 16.9) and Class 2 (mean 41.3 ± 17.3) habitats. Importantly, the mean diameters of Class 3 habitats (mean 8.0 ± 0.98) were considerably larger than Class 2 diameters (mean 7.5 ± 2.3). This result is consistent with over-mature and late-mature trees having a larger crown diameter than regrowth and early mature trees.

**Table 1.** Summary statistics (mean ± sd) for the three mapped habitat classes

| Habitat class | Total area (ha) | Proportion St Marys State Forest (%) | Trees per hectare | Crown cover (%) | Mean crown diameter (m) |
|---|---|---|---|---|---|
| Class 1: Cleared-partially cleared | 204 | 1.2 | 55± 52 | 19.6 ± 16.9 | 6.9 ± 2.3 |
| Class 2: Regrowth-mature | 12,440 | 71.6 | 272 ± 165 | 41.3 ± 17.3 | 7.5 ± 2.3 |
| Class 3: Trace-subdominant | 4,726 | 27.2 | 132 ± 74 | 38.7 ± 18.3 | 8.0 ± 0.98 |

## Accuracy assessment

Traditional site-based accuracy assessment was considered inappropriate for gauging the accuracy of the classified landscape structure where spatial pattern was an important consideration. An alternative approach was adopted involving the following steps:

**Step 1:** Five linear ground transects (60 m x 500 m) were located on a high spatial resolution (0.25 m) digital orthophoto (7 x 3 km) corresponding to the DSMV data (Fig. 3). Line transects were positioned to correspond with observed gradients in tone and texture in the orthophoto, interpretation cues for mapping differences in forest structure (Avery and Berlin 1992).

**Step 2:** Transects were searched for late- and over-mature trees identified by their diameter at breast height (dbh) varying according to tree species (e.g. *C. citriodora*, *E. siderophloia* >60 cm dbh, *E. tereticornis* >90 cm dbh, classed as senescent). Critical dbh values were assessed in the field based on presence of hollows and crown morphology (DNR 1998). The location of senescent trees was recorded with a Garmin GPS and integrated into ArcView GIS 3.2 as point files (ESRI 1999).

**Step 3:** The point file of tree locations was displayed over the digital orthophoto using ArcView 3.2 GIS as a basis for interpreting age classes and class boundaries in the digital orthophoto. Gradients observed from the field transects were subsequently used to interpret (same observers (n = 2) responsible for Step 2) habitat class boundaries in the digital orthophotos. Dark, coarse-texture stands with medium to large crowns were interpreted as Class 3, while lighter-toned stands with uniform small crowns were interpreted as Class 2. Class 1 habitats were distinguishable by a light tone indicating an open structure with well-spaced trees. While these forests have a variegated mosaic structure (McIntyre and Barrett 1992), relatively well-defined boundaries between Class 2 and Class 3 habitats were identifiable on the digital orthophoto based on spatial differences in tone and texture. These interpretation cues were subsequently used to manually digitise habitat class polygons from the digital orthophoto.

**Step 4:** The accuracy of the classified habitat classes derived from the GO model was visually assessed against the habitats interpreted from the orthophoto by:

(a) locating GIS-based transects (n = 93) of varying length (60 - 850 m) wholly within classified Class 2 and Class 3 habitat patches derived from the GO model; and

(b) locating the corresponding transect on the orthophoto-interpreted landscape structure, recording the distance in metres agreeing and disagreeing with (a).

Assessment focused on Class 2 and Class 3 habitats as only a small area of Class 1 occurred within the digital orthophoto coverage (most of Class 1 habitat occurs in the surrounding grazing-agricultural landscapes outside St Marys SF). The respective length of correct and incorrect transect segments located on classified habitat map and the corresponding length of orthophoto transect segments were entered into an error matrix (Congalton 1991). Producer's accuracy (100% - errors of omission) and user's accuracy (100% - errors of commission) were computed for each class, while the overall accuracy of the classification was computed by dividing the total length of correct transect segments falling along the diagonal of the matrix by the total transect segment sampled. KAPPA analysis (Cohen 1960) was performed on the error matrix as the correct formula presented in Hudson and Ramm (1987). The KHAT is defined as:

$$\kappa = \frac{\text{observed accuracy- chance agreement}}{\text{1 - chance agreement}}$$

This statistic serves as an indicator of the extent that the percentage correct values of the error matrix are due to 'true' agreement verses 'chance' agreement (Jensen 1996; Lillesand and Kiefer 1999). The $\kappa$ statistic incorporates off-diagonal elements as a product of the row and column totals and may not agree with the overall mapping accuracy calculated from the error matrix (Jensen 1996). However, it is a useful measure of agreement between the digital orthophoto-interpreted landscape structure and GO model output.

The above accuracy assessment process was repeated for an API classified habitat map (DNR 1998), with the API map compared against the visually interpreted structure observable in the digital orthophoto.

## Stratification of forest types

Twelve floristic associations were identified and mapped from Queensland Department of Primary Industries forest management unit database according to dominant and sub-dominant species (Eyre and Smith 1997). These associations were coded into suitable and unsuitable habitat for the four exudivorous species (Table 2). For these species, unsuitable Class 3 habitats were subsequently reclassified as Class 2 habitats. No floristic stratification was applied for the greater glider due to its non-selective habitat and foraging preferences.

## Results

### Landscape classification

The overall accuracy of the classified GO model habitat data computed from the error matrix was 79.6% (Table 3), while the KHAT statistic was 0.72. Producer's accuracy was relatively high for Class 2 habitats (81.1%) compared to Class 3 habitats (77.0%). User's accuracy, considered a better indicator of class

**Table 2.** Overstorey floristic associations ranked according to habitat preferences of arboreal exudivores

| | |
|---|---|
| *Corymbia citriodora / Eucalyptus siderophloia* | Suitable |
| *E. acmenoides / C. trachyphloia* | Unsuitable |
| *E. fibrosa / C. citriodora* | Suitable |
| *C. intermedia / E. acmenoides* | Unsuitable |
| *C. citriodora / E. crebra* | Suitable |
| *E. siderophloia / E. tereticornis* | Suitable |
| *C. intermedia / E. fibrosa* | Unsuitable |
| *E. moluccana / C. citriodora* | Suitable |
| *Lophostemon / E. tereticornis* | Suitable |
| *E. moluccana / E. tereticornis* | Suitable |
| *C. trachyphloia / E. siderophloia* | Unsuitable |
| *C. intermedia / E. racemosa* | Unsuitable |

accuracy, was higher for Class 3 habitats (83.5%) compared to Class 2 habitats (74.2%). Class 1 habitats, limited to a small number of cleared patches with sharp edges, were mapped with a 100% user's and producer's accuracy.

The API-interpreted landscape structure had a lower overall accuracy (65.6%) compared to the classified GO model data, with a KHAT statistic of 0.37 (Table 4). Producer's accuracy for Class 3 habitats was 78.7% and 60.0% for Class 2 habitats. However, User's accuracy for Class 3 habitats (47.2%) was low compared to Class 2 habitats (85.1%).

**Table 3.** Error matrix of classified landscape structure showing the derivation of producer's and user's accuracy for each habitat type. Classified and visually interpreted field reference data are in metres.

| | Visually interpreted from digital orthophoto | | | | |
|---|---|---|---|---|---|
| Classified Geometric-Optical model habitat data | Trace-subdominant (Class 3) | Regrowth-mature (Class 2) | Cleared (Class 1) | Row total | User's accuracy |
| Trace-subdominant (*Class 3*) | **16597** | 3263 | 0 | 19860 | 83.5% |
| Regrowth-mature (*Class 2*) | 4968 | **14306** | 0 | 19274 | 74.2% |
| Cleared (*Class 1*) | 0 | 0 | **1208** | 1208 | 100% |
| Column total | 21565 | 17569 | 1208 | **32111** | |
| Producer's accuracy | 77.0% | 81.1% | 100% | | |

Overall accuracy = 79.6%   KHAT statistic = 0.72

**Table 4.** Error matrix of API-classified landscape structure showing the derivation of producer's and user's accuracy for each habitat type. Classified and visually interpreted field reference data are in metres.

| | Visually interpreted from digital orthophoto | | | | |
|---|---|---|---|---|---|
| Classified API habitat data | Trace-subdominant (*Class 3*) | Regrowth-mature (*Class 2*) | Cleared (*Class 1*) | Row total | User's accuracy |
| 22461 47.2% (*Class 3*) | Trace-subdominant | | **10610** | 11851 | 0 |
| Regrowth-mature (*Class 2*) | 2866 | **16365** | 0 | 19231 | 85.1% |
| Cleared (*Class 1*) | 0 | 0 | **1208** | 1208 | 100% |
| Column total | 13476 | 28216 | 1208 | **32111** | |
| Producer's accuracy | 78.7% | 60.0% | 100% | | |

Overall accuracy = 65.6%   KHAT statistic = 0.37

The location and overall distribution of Class 3 habitat patches captured in the GO classified landscape structure corresponded well with that visually interpreted from the orthophoto (Fig. 6). However, there were a number of important differences in both landscape composition and spatial pattern.

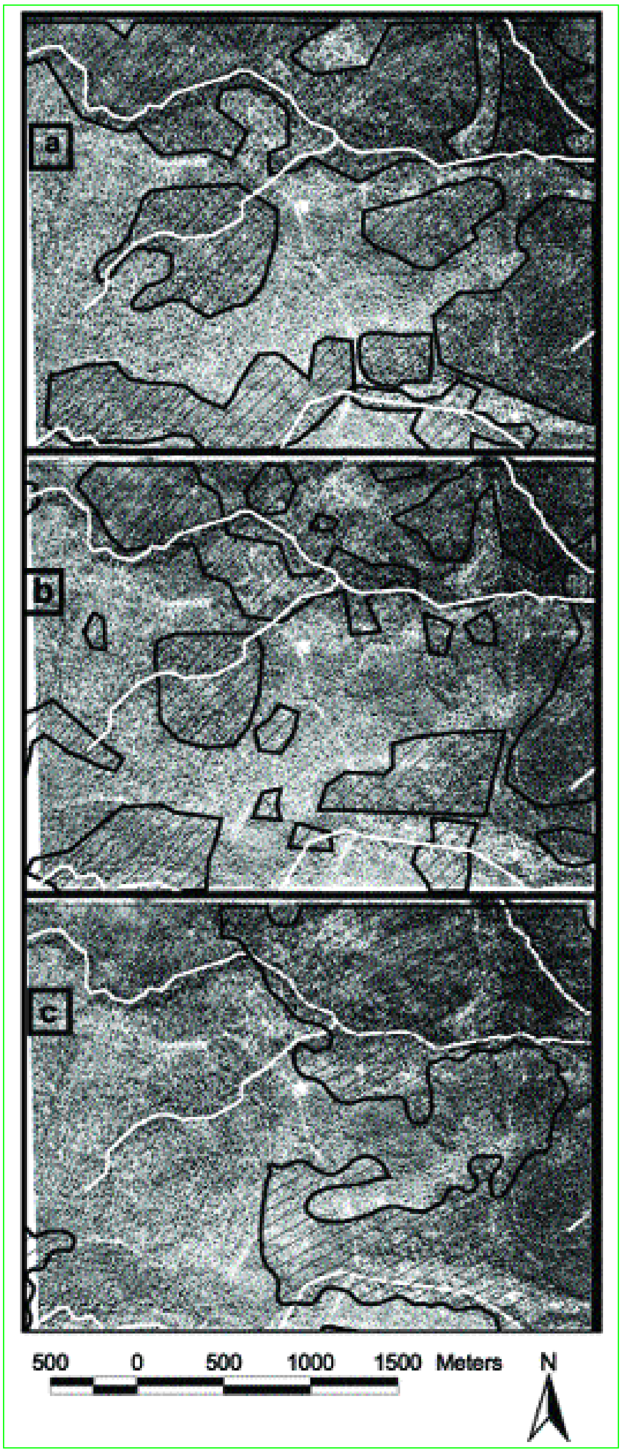


**Figure 6.** Comparison of three landscape structures for a 3200 x 2400 m sub-set of the digital orthophoto coverage. The size, shape and distribution of Class 2 and Class 3 habitats (hatched) were mapped from: (a) visually interpreted digital orthophoto; (b) GO model classification; and (c) API coverage interpreted from 1: 25 000 aerial photographs. There were no Class 1 habitats within the sub-set. White lines represent major drainage lines.

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contrast, the API-interpreted landscape structure (39%) showed a similar proportion of the landscape occupied by Class 3 habitats.

**Table 5.** Comparison of landscape metrics generated for Class 3 habitats for the digital orthophoto coverage (1616 ha). Class 3 habitats have a trace or subdominance of senescent trees. Metrics were generated from: (a) visually interpreted landscape structure derived from the digital orthophoto; (b) GO model classified landscape structure; and (c) API mapped landscape structure.

| Data source | Fraction of landscape (%) | Number of patches | Mean patch size (ha) | Edge density (m ha$^{-1}$) | Mean nearest neighbour distance (m) |
|---|---|---|---|---|---|
| Orthophoto | 40 | 20 | 32.3 | 36 | 55 |
| GO model | 32 | 38 | 13.6 | 36 | 112 |
| API | 39 | 7 | 91.5 | 24 | 429 |

Second, GO model-derived landscape was more fragmented compared to the landscape interpreted from the digital orthophoto (Table 5). For example, the GO model landscape captured 38 patches with a mean patch size of 13.6 ha in comparison to 20 patches with an average size of 32.3 ha for the orthophoto. In contrast, Class 3 habitats captured using API were more aggregated and over-generalised in shape compared to both the GO model-derived and orthophoto-derived landscape structure. This pattern is reflected also in the edge density of Class 3 habitats, with higher edge density in both the orthophoto and the GO model-derived landscape structures compared to the more aggregated API landscape. Finally, the mean nearest neighbour distance, a measure of patch isolation, was substantially higher for the API-derived landscape (429 m) compared to landscape structures mapped from the GO model (112 m) and the digital orthophoto (55 m), reflecting the aggregation of large, but relatively isolated Class 3 habitats.

## Discussion

Moderate-resolution Landsat Thematic data is readily available across Australia at an affordable cost. The total cost of the mapping component of the project (data acquisition, algorithm application, classification, field work and accuracy assessment) was about $10 000. The application of the modified Li-Strahler Geometric Optical model (Scarth *et al*. 2001) to this multi-spectral data, therefore, provides a cost-effective method for accurately mapping the fine-scale age structure of dry eucalypt forests such as those occurring in south-eastern Queensland. We recognise that model outputs require further validation. This shortcoming is being addressed by more detailed field validation of the model's predictions of key forest structural components, including age structure but also vertical structural complexity. Once this work is complete and model outputs fully validated, the GO model has the potential to provide a cost-effective method for assessing and monitoring key structural attributes of the region's dry eucalypt forests over large areas across both the crown-controlled and private forest estate.

As this stage of development and testing, we are confident that the model is capable of providing the necessary habitat information for the reliable assessment of habitat loss effects on arboreal marsupial populations living in these dry forest landscapes. Structural Class 3 represents forest stands with a trace or subdominance of hollow-bearing trees, a limiting resource for arboreal marsupials. Class 3 spotted-gum/ironbark habitats also provide an important food source for exudivorous species, especially the yellow-bellied glider, with old spotted gum trees exuding sap when incised (Goldingay and Kavanagh 1991; Eyre and Smith 1997). The validity of the mapping is confirmed by the results of the analysis (McAlpine and Eyre 2000), which found a strong positive relationship between the proportion of the landscape occupied by Class 3 spotted-gum/ironbark habitats and the count of yellow-bellied gliders. Similar but weaker relationships were identified for the diversity of exudivorous arboreal species. The greater glider was dominated by site-scale rather than landscape-scale habitat influences.

The methods did however underestimate the total area of Class 3 (trace-subdominant) habitats, and failed to accurately map patch size and shape. These limitations need to be taken into account in indicator development. The underestimation of the proportion of Class 3 habitats directly impacts on the assessment of the effect of habitat loss and the presence of thresholds (*sensu* Andrén 1994), across which small changes in the amount of critical habitat produce abrupt shifts in population response. The amount of Class 3 habitat can be upwardly adjusted in assessing the significance of the results, provided the rate of underestimation is spatially consistent across the whole forest. The results of the accuracy assessment and comparison with field observations confirm this to be the case. The problem of accurately mapping the size and shape of Class 3 habitat patches, however, also constrains our ability to reliability report on the ecological significance of landscape pattern (e.g. patch size, shape, edge, nearest neighbour metrics) for Montreal Process indicator 1.1e. for the St Marys case study.

The accuracy of the model outputs can be improved in a number of ways. First, by sensitising the GO model to take into account differences in stand structural morphology across forest types. This refinement can be achieved by: (i) careful measurement of key structural attributes such as mean crown diameter and stems per hectare for dominant forest types (e.g. *C. citriodora*/ironbark floristic associations compared to those dominated by *E. acmenoides* and *C. intermedia* and/or *C. trachyphloia*); and (ii) the stratified application of the model according to forest types found to have significant structural differences.

Second, more sophisticated classification routines (e.g. decision trees) can also be developed which apply decision rules for classification based on observed differences in mean crown diameter, trees per hectare and crown cover percent for the three structural classes and also by forest type. This improvement will allow a more precise definition of habitat class structural boundaries and so avoid the less precise definition generated by the automated classification routine. Additional structural parameters such as shaded and sunlight canopy (Scarth *et al*. 2001) can be tested for their structural and ecological significance and added to the classification/stratification process if warranted.

Third, height is an important structural attribute characterising differences in the age structure of dry eucalypt forests. A number of methods have been trialed to incorporate height into the classification/stratification process. The first uses digital soft photogrammetric parallax-based measurements derived from scanned 1:25 000 aerial photographs (Scarth *et al*. 2001) and a high-resolution digital terrain model to quantify the mean canopy height at a spatial resolution of 10 m. It has the capacity to cost-effectively map canopy height over large areas, but is limited by the difficulty of obtaining reliable ground control points (especially height values) in often featureless forest landscapes. The second method (Tickle *et al.* 1998b; Witte *et al.* 2000) employs a helicopter-based laser-scanner device for measuring tree height in St Marys State Forest. This method showed a strong correspondence ($R^2$ = 0.97) with ground-measured tree height (*n* = 80) with the slope of the linear regression line 0.89, demonstrating that it is capable of providing reliable height data. However, while the laser scanner is technically capable of capturing tree height data over a whole forest, the spatial extent of actual coverage is very much dependent on available funding.

The approach adopted by this study differs from procedures for mapping tree clusters using 2 m spatial resolution Digital Multi Spectral Video (DSMV) data (Preston and Moore 2000). The high-resolution method applies a tree cluster delineation algorithm to the red and near-infrared spectral bands to delineate spatially adjacent or merged tree crowns that are spectrally distinct. The algorithm quantifies geometric attributes of large individual trees and clusters of smaller trees in the upper and mid-stratums. A range of decision tree models is applied to identify tree species and key structural attributes including crown radius and growth stage. This approach is data and computationally intensive, and has proved more reliable in mature temperate eucalypt forests compared to the sub-tropical eucalypt forests such as St Marys SF. The high-resolution approach differs in a number of ways with GO model approach in that it requires the identification of the species and key structural attributes of individual trees/clusters (Preston and Moore 2000). These attributes are then aggregated to determine the age structure of individual stands. In contrast, the GO model uses area-weighted combinations of reflectances from sunlit canopy, sunlight background, shaded canopy and shaded background components to capture the key structural properties of one-hectare stands without having to identify individual trees/clusters and tree species. This is an important advantage for dry eucalypt forests such as St Marys SF where stands are composed of a heterogenous mix of trees of different species and age varying in height, crown morphology and spacing. The greater the species diversity and the more variable the age structure, the more difficult is the task of high-resolution mapping.

## Conclusion

The aim of this study was to apply a modified Li and Strahler (1992) Geometric Optical model developed by Scarth *et al.* (2001) to map forest age structure within St Marys SF in a way that was meaningful to the ecology of four exudivore arboreal species and one arboreal folivore (*P. volans*). This was achieved to an overall accuracy of 79%, but was limited by an inability to accurately capture the size and shape of habitat patches dominated by a trace or a sub-dominance of over-mature or senescent trees. However, this limitation aside, it represented a major improvement on the API-interpreted age structure. The model's accuracy, however, can be improved by sensitising the model parameters for floristic differences in stand morphology, and by the inclusion of additional structural parameters, notably tree height. This represents an important step towards developing and testing Montreal Process Indicator 1.1e in the selectively logged, dry eucalypt forests of south-eastern Queensland.

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