# Modelling Forest Species Using Lidar-Derived Metrics of Forest Canopy Gaps

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## Abstract

*LiDAR intensity and texture features have reported high accuracies for discriminating forest species, particularly with the utility of the random forest (RF) algorithm. To date, limited studies has utilized LiDAR-derived forest gap information to assist in forest species discrimination. In this study, LiDAR intensity and texture features were extracted from forest canopy gaps to discriminate Eucalyptus grandis and Eucalyptus dunnii within a forest plantation. Additionally, LiDAR intensity and texture information was extracted for both canopy gaps and forest canopy and utilized for species discrimination. Using LiDAR intensity and texture information extracted for both canopy gap and forest canopy, resulted in a model accuracy of 94.74% (KHAT = 0.88). Using only canopy gap information, the RF model obtained an overall accuracy of 90.91% (KHAT = 0.81). The results highlight the potential for using canopy gap information for commercial species discrimination and mapping.*

## 1. Introduction and Literature Review

The importance of forest species discrimination and mapping has been reported by a number of studies (see for example Dalponte *et al.* 2012; Peerbhay *et al.* 2013; Peerbhay *et al.* 2014; Waser *et al.* 2015; Qin *et al.* 2016; Mulyani and Jepson 2017). The ability to discriminate forest species has both economic and conservation benefits (Kim *et al.* 2009; Shang and Chrisholm 2014). Economically, forest species information assists in estimating biomass and wood production, and is important to develop growth and yield models (Ko *et al.* 2013). Additionally, species information enables estimating timber volume; invaluable for commercial plantations (Dalponte *et al.* 2008).

In conservation, forest species mapping is important for the management of forest communities as well as promoting effective assessment of species vulnerability to threats such as pests or drought (Hill *et al.* 2010; Shang and Chrisholm 2014; Abdollahnejad *et al.* 2017). Furthermore, forest species mapping enables biodiversity maintenance and stem volume estimation (Barilotti *et al.* 2009), sustainable forest management (Falkowski *et al.* 2009), forest disturbance detection (Waser *et al.* 2015), as well as habitat mapping (Immitzer *et al.* 2012).

Traditionally, field surveys were the main approaches to acquiring information about forest species (Immitzer *et al.* 2012). These methods are however costly, labour intensive, and time consuming (Cho *et al.* 2012; Peerbhay *et al.* 2013). Remote sensing provides a more cost-effective and less labour-intensive approach compared with traditional in situ methods (Bradley and Fleishman 2008; Cho *et al.* 2012). Remote sensing is able to map large forested areas at high spatial resolutions (Xie *et al.* 2008; Immitzer *et al.* 2012). Additionally, passive remote sensing imaging sensors, such as satellite electro-optical scanners, have a number of spectral bands to assist in more precise tree species discrimination (Arenas-Castro *et al.* 2013). Passive sensors capture information using solar illumination or energy emitted from the Earth's surface (Chuvieco and Huete 2010; Erdle *et al.* 2011).

Subsequently, a number of studies have utilized passive imaging sensors to classify forest species. For example, Mallinis *et al.* (2008) used Quickbird imagery to classify dominant forest vegetation in North Greece using an object-based approach and three classification methods including nearest neighbour, classification trees, and a combination of classification trees and local indicators of spatial association (texture features). The best overall accuracy (78.11%) and KHAT statistic (0.75) was obtained using classification trees with texture features. More recently, Abdollahnejad *et al.* (2017) used Quickbird imagery to discriminate dominant tree species in Gorgan city, Iran using random forest (RF), support vector machines (SVM), and k-nearest neighbour (*k*-NN). Of the three classifiers, RF was the most efficient, yielding an overall accuracy of 63.85%.

Very high spatial resolution imagery has been widely used to discriminate forest species. However, similarity of species' spectral reflectance is still a limiting factor (Lucas *et al.* 2008; Hill *et al.* 2010; Korpela *et al.* 2010). Data from active, non-imaging sensors such as light detection and ranging (LiDAR), overcomes this spatial limitation, and are subsequently capable of discriminating forest species more efficiently compared with imaging sensors (Ke *et al.* 2010). The advantage of LiDAR is the provision of three dimensional and species-specific structural information (Ke *et al.* 2010; Kim *et al.* 2011). For example, Kim *et al.* (2009) classified seven coniferous and eight broadleaved tree species using two LiDAR datasets, i.e. one for leaf-on and one for leaf-off conditions. Using intensity features and a linear discriminant function, the authors reported accuracies of 83.4% and 73.1% for leaf-off and leaf-on datasets, respectively. The authors further tested a combination of both datasets and obtained an improved overall classification accuracy of 90.6%. Ørka *et al.* (2009) classified coniferous and deciduous tree species using intensity and structural features (i.e. normalized height features, canopy penetration depth, and crown density features) and linear discriminant analysis. Classification accuracies ranged from 70%, using intensity features, to 88%, using a combination of intensity and structural features.

Vauhkonen *et al.* (2009) and Li *et al.* (2013) tested the utility of texture information for forest species discrimination. In addition to texture features, Vauhkonen *et al.* (2009) derived tree crown approximations such as alpha shape, height, and intensity to discriminate between Scandinavian commercial species (i.e. pine, spruce, and deciduous species). Using a discriminant analysis classifier and a combination of intensity and texture features, the authors obtained an overall classification accuracy of 91% and KHAT of 0.84. Li *et al.* (2013) assessed the utility of texture features and tree crown characteristics (three-dimensional texture, relative degree of foliage clustering, relative scale of foliage clustering, and gap distribution within tree crowns) to classify four forest species (i.e. sugar maple, trembling aspen, jack pine, and eastern white pine) in Ontario, Canada. Using a linear discriminant analysis, the authors reported a classification accuracy of 77.5% and KHAT of 0.7.

Several studies have successfully used LiDAR derivatives and the RF classifier for forest species discrimination. For example, Korpela *et al.* (2010) used linear discriminant analysis, *k*-NN, and RF with various intensity features to discriminate Scots pine, Norway spruce, and birch. Using a combination of two discrete LiDAR datasets, overall classification accuracies ranged from 89.4% to 90.8%, with RF obtaining an improved overall accuracy of 90.8% and KHAT of 0.84. Similarly, Yu *et al.* (2014) utilized RF to discriminate between Scots pine, Norway spruce and birch. The authors assessed the efficiency of using a combination of full-waveform and discrete LiDAR features including mean heights, standard deviation of heights, and a mean of full-waveform data interacting with a tree. Using a combination of waveform and discrete LiDAR features yielded the highest classification accuracy of 73.4%. Cao *et al.* (2016) utilized RF to discriminate six forest species using full-waveform LiDAR. Overall accuracies ranged from 68.6% to 75.8%, with KHAT values ranging from 0.62 to 0.68.

In South Africa, *Eucalyptus* is an important commercial forest species, with *Eucalyptus grandis* being the dominant commercial hardwood species, accounting for approximately 48% of all total hardwood area (DAFF 2012). Discriminating *Eucalyptus* species effectively using remote sensing would, therefore, be beneficial to the commercial forestry industry. To date, no study has investigated the utility of canopy gap information for species discrimination, albeit Li *et al.* (2013), who looked at gaps between tree crowns. Consequently, this study investigates the utility of canopy gap LiDAR-derived intensity and texture features for discriminating *Eucalyptus grandis* and *Eucalyptus dunnii* using the RF classifier.

## 2. Materials and Methods

### 2.1. Study Area

The study was undertaken at the Sappi Riverdale plantation; an area of 5 999ha located near Richmond in KwaZulu-Natal, South Africa (Figure 1). *Eucalyptus* comprises three species, namely, *E. grandis*, *E. smithii,* and *E. dunnii*, of which only *E. grandis* ($n$ = 15) and *E. dunnii*, ($n$ = 10) were used in this study (Macfarlane 2006). The species and respective ages for each compartment is shown in Table 1. Table 1 also indicates the total number of canopy gaps present per compartment.

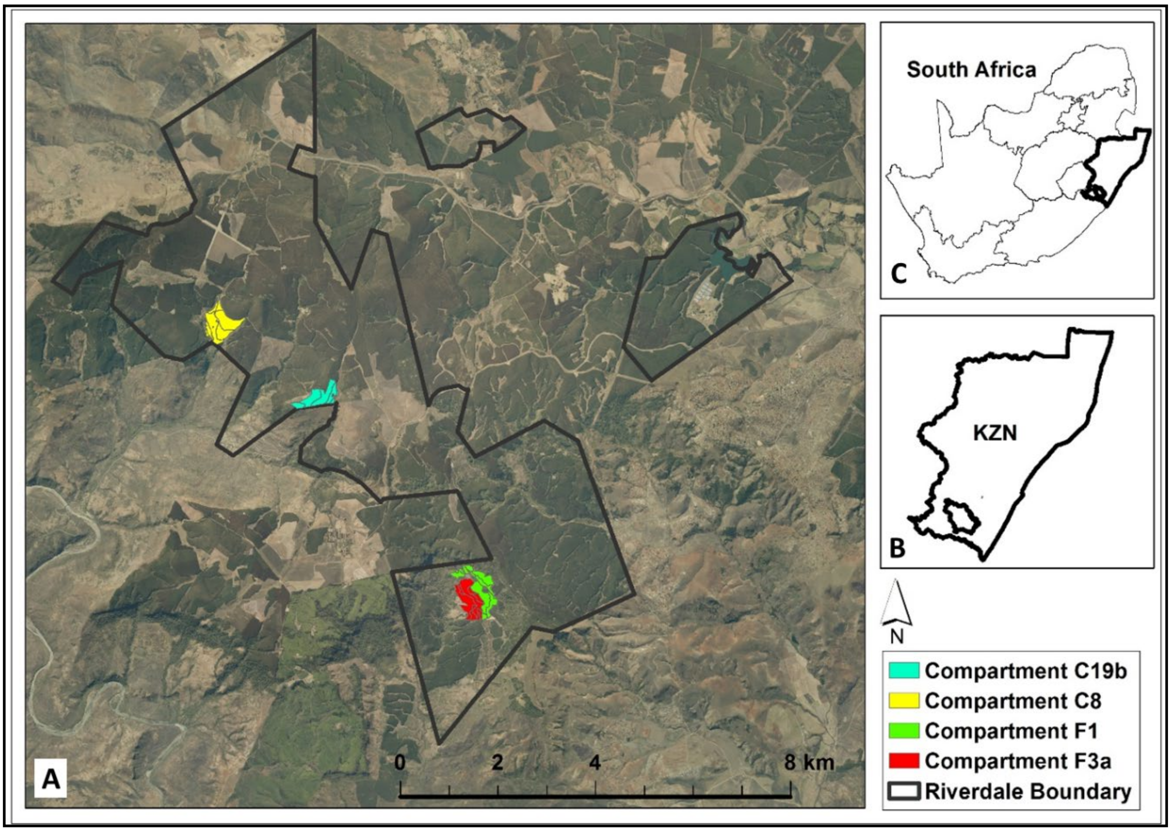


Figure 1. The Sappi Riverdale plantation is (a) located in KwaZulu-Natal (b), South Africa (c). Background image is ESRI ArcGIS online's 50cm colour imagery for South Africa.

Table 1. The four *Eucalyptus* compartments selected for this study.

| **Species** | **Compartment** | **Age (years)** | **Tree height (m)** | **Number of gaps** |
|---|---|---|---|---|
| ***E. dunnii*** | C19b | 2.48 | 10.08 | 59 |
| | C8 | 5.24 | 15.95 | 39 |
| ***E. grandis*** | F1 | 4.81 | 21.92 | 54 |
| | F3a | 4.38 | 21.05 | 68 |

## 2.2. LiDAR and Field Data

All LiDAR and field data were supplied by Sappi Forests. LiDAR data were acquired 15 – 22 March 2014 using a Leica ALS50-2 scanner (Table 2). Field data was supplied in the form of enumerated plot data for each compartment. For each compartment, LiDAR metrics were derived for both forest canopy and canopy gaps. To ensure a balanced sample size for RF analysis, 30 canopy gaps were randomly selected for each compartment. Additionally, 30 forest canopy samples were randomly selected. A total of 60 samples were subsequently used for the analysis.

Table 2: LiDAR data capture information.

| | |
|---|---|
| Number of returns | 4 |
| Pulse rate (Hz) | 1260 000 |
| Scan rate (Hz) | 53 |
| Average flying height (m) | 820 |
| Survey period | 15 to 22 March 2014 |

## 2.3. Deriving LiDAR Metrics

### *2.3.1. Intensity Features*

To discriminate *E. grandis* and *E. dunnii*, various intensity features ($n$ = 34) were calculated using the GridMetrics tool available in FUSION/LDV v3.60 (Yunfei *et al.* 2008; Maltamo *et al.* 2014; FUSION 2016). FUSION/LDV is a software package developed to view, analyse, and extract LiDAR returns and descriptive statistics (features) thereof. The intensity features included; Total return count above minimum height, Minimum, Maximum, Mean, Mode, Standard deviation, Variance, Coefficient of variance, Interquartile distance, Skewness, Kurtosis, Average absolute deviation, L-moments (L1 – L4), L-moment coefficient of variance, L-moment skewness, L-moment kurtosis, and P01 – P99. FUSION/LDV has previously been used in an array of forest applications including tree species differentiation using LiDAR intensity data (Kim *et al.* 2009), individual tree genera classification (Kim *et al.* 2011), deriving a variety of LiDAR elevation metrics for estimating forest biomass and identifying low-intensity logging areas (d'Oliveira *et al.* 2012), and deriving various LiDAR metrics to assist in predicting live and dead tree basal areas (Bright *et al.* 2013).

The GridMetrics tool uses command line programs to extract specific LiDAR return information. The tool outputs a csv (comma delimited) file containing intensity features ($n$ = 34) for each LiDAR input cell. Each intensity feature in csv format was subsequently converted to ASCII grid format with a cell size of 1m using the CSV2Grid tool. This was achieved by specifying the column heading using the command line prompt corresponding to a specific intensity feature. Subsequently, the intensity features in ASCII grid format was used in ArcMap v10.3.1 to extract the intensity information for forest canopy ($n$ = 30) and canopy gap ($n$ = 30), for each of the four compartments (ESRI 2015; FUSION 2016).

### *2.3.2. Texture Features*

In addition to intensity features, texture features ($n$ = 12) were calculated for all four compartments using eCognition developer 9 (Trimble 2016). Prior to extracting texture features, a multiresolution segmentation (MRS) was undertaken to derive object features using the combined LiDAR canopy height model (CHM) and intensity raster. MRS is a region merging algorithm that derives image objects from pixels (Belgiu and Drăguţ 2014). Image objects are iteratively merged and determined by some homogeneity criteria (Rahman and Saha 2008). The homogeneity criteria comprise scale, compactness, and a shape parameter (Drăguţ *et al.* 2010). Scale determines the size of resulting objects, whereas shape and compactness determine the overall shape and compactness of resulting objects (Definiens 2007; Rahman and Saha 2008). We applied a scale factor of 5, and shape and compactness values of 0.1 and 0.5 respectively (Lombard *et al.* 2017).

Eight grey-level co-occurrence matrices (GLCM) including Angular 2$^{nd}$ moment, Contrast, Correlation, Dissimilarity, Entropy, Homogeneity, Mean, and Standard deviation, and four grey-level difference vector (GLDV) texture features including Angular 2$^{nd}$ moment, Contrast, Entropy, and Mean were calculated on the resulting image objects. Texture measures the differences in levels or grey tone of objects (Haralick *et al.* 1973). GLCM measures the spatial relationships of co-occurrence grey levels at specific distances and directions, whereas GLDV measures GLCM diagonals (Mhangara and Odindi 2013; Dian *et al.* 2015). Similar to intensity feature extraction, texture features were extracted for forest canopy ($n$ = 30) and canopy gap ($n$ = 30) for all the four compartments using ArcMap v10.3.1 (ESRI 2015).

### 2.4. Species Classification Using Random Forest

Using the extracted intensity ($n$ = 34) and texture ($n$ = 12) features, a random forest (RF) classification was employed to discriminate *E. grandis* and *E. dunnii*. RF is an ensemble classifier that builds a large number of decision trees (*ntree*) (Breiman 2001). At each node split, a bootstrap sample (*mtry*) of the original data is selected, and used to grow (*ntree*) classification trees (Breiman 2001). The final prediction is based on a majority vote of *ntree* predictions (Liaw and Wiener 2002). In this study, *ntree* = 500 and *mtry* = square root of the number of features used for node splitting within each tree was used (Belgiu and Drăguţ 2016). Additionally, the input dataset was split, with 70% of the data used for training, and the remaining 30% used as an independent test set. To evaluate the influence of tree age on classification accuracy, we modelled combinations of compartments as follows: compartment C19b compared with compartment F3a, compartment C8 with compartment F1, compartment C19b with compartment F1, and compartment C8 with compartment F3a. The RF ensemble was implemented using the randomForest package in R version 3.4.1 (Liaw and Wiener 2002; R Development Core Team 2017).

### 2.5. Accuracy Assessment

RF model accuracy was assessed using a confusion matrix. The out of bag (OOB) error estimate, based on the 30% sample, was utilized to estimate training model accuracy whereas the test accuracy was assessed using overall accuracy (OA), based on the 70% sample (Cao *et al.* 2016). Additionally, the KHAT statistic was used as an independent measure of model performance. KHAT (Equation 1) assesses chance agreement against actual classification agreement and is defined according to the following formula (Congalton and Green 2009):

$$\widehat{K} = \frac{P_O - P_C}{1 - P_C} \qquad [1]$$

Where: $P_o = \sum_{i=1}^{k} P_{ii}$ is the actual agreement and $P_c = \sum_{i=1}^{k} P_{i+} P_{+j}$ is the chance agreement.

## 3. Results

In this study, the RF classifier was used to discriminate *E. grandis* and *E. dunnii* using LiDAR-derived intensity and texture features. Classification was undertaken using texture features, intensity features, and a combination of texture and intensity features. The respective feature sets were evaluated for canopy gaps and a combination of forest canopy and canopy gaps. We further examined the effect of age on the ability to discriminate *E. grandis* and *E. dunnii* by using both similar aged and differing aged compartments.

Table 3 shows the results for discriminating *E. grandis* and *E. dunnii* using LiDAR derived intensity and texture features. Overall classification accuracies ranged from 59.09% (KHAT = 0.14) to 94.74% (KHAT = 0.88). Classification using canopy gap intensity and texture features yielded accuracies ranging from 59.09% (KHAT = 0.14) to 90.91% (KHAT = 0.81). The highest classification accuracy was obtained using a combination of intensity and texture features ($n$ = 46), whereas the lowest accuracy was obtained using texture features ($n$ = 12).

Using a combination of canopy gap and forest canopy intensity and texture features resulted in improved classification accuracies. However, similar to the results obtained using canopy gap intensity and texture features, using texture features ($n$ = 12) yielded the lowest accuracy (65.62%; KHAT = 0.31) whereas using a combination of texture and intensity features yielded the highest accuracy (94.74%; KHAT = 0.88).

A closer evaluation of the results revealed differences in classification accuracy when discriminating the relative age between tree species. For example, the best classification accuracy (94.74%; KHAT = 0.88) was obtained for the discrimination of compartments C19b (*E. dunnii*) and F3a (*E. grandis*) that had an age difference of 1.9 years. Conversely, a significantly lower classification accuracy (72.22%; KHAT = 0.45) was obtained for the discrimination of compartments C8 (*E. dunnii*) and F1 (*E. grandis*) that had an age difference of just 0.43 years. Additional evidence of this finding can be seen when comparing the classification accuracy of compartments C19b and F3a (94.74%; KHAT = 0.88) with compartments C8 and F3a (77.78%; KHAT = 0.56). The age difference between compartments C8 and F3a is 0.86 years. These results suggest that tree age influences the ability to discriminate *E. grandis* and *E. dunnii*. Additionally, tree age is related to tree height, which results in variable texture (Kayitakire *et al.* 2006).

Table 3. Classification of *E. grandis* and *E. dunnii* using LiDAR derived intensity and texture features.

| | | **C19b and F3a** | | | | **C8 and F1** | | | | **C19b and F1** | | | | **C8 and F3a** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Train** | | **Test** | | **Train** | | **Test** | | **Train** | | **Test** | | **Train** | | **Test** | |
| **Extracted from** | **Feature set** | **OOB error** | **KHAT** | **OA** | **KHAT** | **OOB error** | **KHAT** | **OA** | **KHAT** | **OOB error** | **KHAT** | **OA** | **KHAT** | **OOB error** | **KHAT** | **OA** | **KHAT** |
| **Canopy gap** | **Intensity & Texture ($n$ = 46)** | 7.89 | 0.84 | 90.91 | 0.81 | 30.23 | 0.39 | 64.71 | 0.29 | 8.89 | 0.82 | 86.67 | 0.73 | 19.05 | 0.61 | 77.78 | 0.5 |
| | **Intensity ($n$ = 34)** | 21.43 | 0.57 | 77.78 | 0.54 | 28.57 | 0.43 | 66.67 | 0.33 | 29.17 | 0.42 | 66.67 | 0.25 | 17.95 | 0.64 | 80.95 | 0.61 |
| | **Texture ($n$ = 12)** | 13.04 | 0.74 | 85.71 | 0.71 | 38.1 | 0.24 | 61.11 | 0.22 | 12.5 | 0.75 | 85 | 0.7 | 34.21 | 0.28 | 59.09 | 0.14 |
| **Combination of forest canopy and canopy gap** | **Intensity & Texture ($n$ = 46)** | 3.66 | 0.92 | 94.74 | 0.88 | 28.4 | 0.43 | 71.79 | 0.43 | 8.14 | 0.84 | 91.18 | 0.82 | 16 | 0.68 | 77.78 | 0.56 |
| | **Intensity ($n$ = 34)** | 19.1 | 0.62 | 80.65 | 0.61 | 26.19 | 0.48 | 72.22 | 0.45 | 29.11 | 0.42 | 68.29 | 0.36 | 13.64 | 0.73 | 84.38 | 0.69 |
| | **Texture ($n$ = 12)** | 15.48 | 0.69 | 83.33 | 0.67 | 30.68 | 0.39 | 65.62 | 0.31 | 8.7 | 0.83 | 85.71 | 0.71 | 27.27 | 0.46 | 68.75 | 0.37 |

## 4. Discussion

This study evaluated the potential to discriminate two *Eucalyptus* species, i.e. *E. grandis* and *E. dunnii* within a commercial plantation using LiDAR derived intensity and texture features and the RF classifier. Specifically, we evaluated the utility of canopy gaps to classify *E. grandis* and *E. dunnii* and further examined the influence of tree age on model performance.

Forest species classification has traditionally been undertaken using ground-based methods and aerial imagery captured using passive imaging sensors (Donoghue *et al.* 2007; Dalponte *et al.* 2008; Puttonen *et al.* 2010). However, more accurate forest species information is invaluable for commercial forestry as well as conservation sectors (Moffiet *et al.* 2005; Puttonen *et al.* 2010). Recent studies (see for example Vaughn *et al.* 2012; Yu *et al.* 2014; Cao *et al.* 2016) have reported improved accuracies for forest species discrimination using LiDAR data; specifically using forest canopy information. However, in this study, LiDAR derived intensity and texture features yielded comparable accuracies using forest canopy gaps information; highest accuracy of 90.91% (KHAT = 0.81), and improved accuracies when using forest canopy gap and forest canopy information; highest accuracy of 94.74 (KHAT = 0.88).

The RF classifier has been documented to yield accurate forest species discrimination results and often outperform other ensemble learners. LiDAR, in combination with RF, is particularly useful for forest species classification as shown in literature (Korpela *et al.* 2010; Yu *et al.* 2014; Adelabu and Dube 2015; Cao *et al.* 2016). This study has demonstrated that using the RF classifier and LiDAR intensity and texture information contained within forest canopy and canopy gaps can accurately discriminate forest species.

Forest species discrimination using RF and a combination of LiDAR intensity, texture features and canopy gaps yielded an overall accuracy of 90.91% (KHAT = 0.81). The results of this study compare favourably with Korpela *et al.* (2010), who used various intensity features and obtained an overall accuracy of 90.8% (KHAT = 0.84). Using a combination of intensity and texture features yielded higher accuracies than Yu *et al.* (2014), who obtained an overall accuracy of 73.4% using a combination of full-waveform and discrete LiDAR features. Our results are also higher than Cao *et al.* (2016), with an overall accuracy of 75.8% and KHAT = 0.68 for discriminating Masson pine, Chinese fir, Slash pines, Sawtooth oak, Sweet gum, and Chinese holly using full-waveform LiDAR features. The findings of this study suggest that using both intensity and texture features derived from discrete LiDAR can readily be used for accurate species classification.

## 5. Conclusion

The overarching aim of this study was to evaluate the potential of using canopy gap information in aiding forest species mapping. To this end, LiDAR intensity and texture features extracted from canopy gaps was successfully employed to model *E. grandis* and *E. dunnii* within a commercial plantation. The majority of literature utilized forest canopy information for species classification.

Therefore, this work presents novelty, particularly within South Africa. Additionally, the developed framework displayed robustness within a forestry plantation and the efficiency of the results may be of interest to forest managers and fellow researchers.

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## 7. References

Abdollahnejad A, Panagiotidis D, Joybari S & Surový P 2017, 'Prediction of Dominant Forest Tree Species Using QuickBird and Environmental Data', *Forests*, vol. 8, no. 2.

Adelabu S & Dube T 2015, 'Employing ground and satellite-based QuickBird data and random forest to discriminate five tree species in a Southern African Woodland', *Geocarto International*, vol. 30, no, 4, pp. 457-471.

Arenas-Castro S, Yulien Y, Jiménez-Muñoz J, Sobrino J, Fernández-Haeger J & Jordano-Bardudo D 2013, Mapping wild pear trees (*Pyrus bourgaeana*) in Mediterranean forest using high-resolution QuickBird satellite imagery, *International Journal of Remote Sensing*, vol. 34, nos, 9-10, pp. 3376-3396.

Barilotti A, Crosilla F & Sepic F 2009, 'Curvature analysis of LiDAR data for single tree species classification in alpine latitude forests', in Bretar F, Pierrot-Deseilligny M & Vosselman G (eds.), *Laser scanning,* Proceedings of the IAPRS held 1-2 September 2009, Paris, France: International Archives of Photogrammetry and Remote Sensing.

Belgiu M & Drăguţ L 2014, 'Comparing supervised and unsupervised multiresolution segmentation approaches for extracting buildings from very high resolution imagery', *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 96, pp. 67-75.

Belgiu M & Drăguţ L 2016, 'Random forest in remote sensing: A review of applications and future directions', *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 114, pp. 24-31.

Bright B, Hudak A, McGaughey R, Andersen H & Negrón J 2013, 'Predicting live and dead tree basal area of bark beetle affected forests from discrete-return lidar', *Canadian Journal of Remote Sensing*, vol. 39, no. S1, pp. S99-S111.

Bradley B & Fleishman E 2008, 'Can remote sensing of land cover improve species distribution modelling?', *Journal of Biogeography*, vol. 35, pp. 1158-1159.

Breiman L 2001, 'Random Forests', *Machine Learning*, vol. 45, pp. 5-32.

Cao L, Coops N, Innes J, Dai J, Ruan H & She G 2016, 'Tree species classification in subtropical forests using small-footprint full-waveform LiDAR data', *International Journal of Applied Earth Observation and Geoinformation,* vol. 49, pp. 39-51.

Cho M, Mathieu R, Asner G, Naidoo L, van Aardt J, Ramoelo A, Debba P, Wessels K, Main R, Smit I & Erasmus B 2012, 'Mapping tree species composition in South African savannas using an integrated airborne spectral and LiDAR system', *Remote Sensing of Environment*, vol. 125, pp. 214-226.

Congalton R & Green K 2009, *Assessing the accuracy of remotely sensed data: principles and practices*, 2nd ed, CRC Press, Boca Raton.

Chuvieco E & Huete A 2010, *Fundamentals of satellite remote sensing,* Taylor & Francis Group, Boca Raton.

DAFF 2012, *Report on commercial timber resources and primary roundwood processing in South Africa 2011/2012*, Department of Agriculture, Forestry and Fisheries, Pretoria.

Dalponte M, Bruzzone L & Gianelle D 2008, 'Fusion of Hyperspectral and LIDAR Remote Sensing Data for Classification of Complex Forest Areas', *IEEE Transactions on Geoscience and Remote Sensing*, vol. 46, no. 5, pp. 1416-1427.

Dalponte M, Bruzzone L & Gianelle D 2012, 'Tree species classification in the Southern Alps based on the fusion of very high geometrical resolution multispectral/hyperspectral images and LiDAR data', *Remote Sensing of Environment*, vol. 123, pp. 258-270.

Definiens 2007, *Definiens Developer 7- User Guide*, Definiens AG, München.

Dian Y, Li Z & Pang Y 2015, 'Spectral and Texture Features Combined for Forest Tree species Classification with Airborne Hyperspectral Imagery', *Journal of Indian Society of Remote Sensing*, vol 43, no. 1, pp. 101-107.

d'Oliveira M, Reutebuch S, McGaughey R & Andersen H 2012, 'Estimating forest biomass and identifying low-intensity logging areas using airborne scanning lidar in Antimary State Forest, Acre State, Western Brazilian Amazon', *Remote Sensing of Environment*, vol. 124, pp. 479-491.

Donoghue D, Watt P, Cox N & Wilson J 2007, 'Remote sensing of species mixtures in conifer plantations using LiDAR height and intensity data', *Remote Sensing of Environment,* vol. 110, pp. 509-522.

Drăguţ L, Tiede D & Levick S 2010, 'ESP: a tool to estimate scale parameter for multiresolution image segmentation of remotely sensed data', *International Journal of Geographical Information Science*, vol. 24, no. 6, pp. 859-871.

Erdle K, Mistele B, & Schmidhalter U 2011, 'Comparison of active and passive spectral sensors in discriminating biomass parameters and nitrogen status in wheat cultivars', *Field Crops Research*, vol. 124, pp. 74-84.

ESRI 2015, *ArcGIS Pro [online]*, viewed 18 March 2017, <http://pro.arcgis.com>.

Falkowski M, Evans J, Martinuzzi S, Gessler P & Hudak A 2009, 'Characterizing forest succession with lidar data: An evaluation for the inland Northwest, USA', *Remote Sensing of Environment*, vol. 113, pp. 946-956.

FUSION 2016, *FUSION [online]*, University of Washington, Seattle, viewed 3 June 2017, <http://forsys.cfr.washington.edu/fusion/fusionlatest.html>.

Haralick R, Shanmugam K & Dinstein I 1973, 'Textural Features for Image Classification', *IEEE Transactions on Systems, Man and Cybernetics*, vol. 3, no. 6, pp. 610-621.

Hill R, Wilson A, George M & Hinsley S 2010, 'Mapping tree species in temperate deciduous woodland using time-series multi-spectral data', *Applied Vegetation Science*, vol. 13, pp. 86-99.

Immitzer M, Atzberger C & Koukal T 2012, 'Tree Species Classification with Random Forest Using Very High Spatial Resolution 8-Band WorldView-2 Satellite Data', *Remote Sensing*, vol. 4, pp. 2661-2693.

Kayitakire F, Hamel C & Defourny P 2006, 'Retrieving forest structure variables based on image texture analysis and IKONOS-2 imagery', *Remote Sensing of Environment*, vol. 102, pp. 390-401.

Ke Y, Quackenbush L & Im J 2010, 'Synergistic use of QuickBird multispectral imagery and LIDAR data for object-based forest species classification', *Remote Sensing of Environment*, vol. 114, pp. 1141-1154.

Kim S, McGaughey R, Andersen H & Schreuder G 2009, 'Tree species differentiation using intensity data derived from leaf-on and leaf-off airborne laser scanner data', *Remote Sensing of Environment*, vol. 113, pp. 1575-1586.

Kim S, Hinckley T & Briggs D 2011, 'Classifying individual tree genera using stepwise cluster analysis based on height and intensity metrics derived from airborne laser scanner data', *Remote Sensing of Environment*, vol. 115, pp. 3329-3342.

Ko C, Sohn G & Remmel T 2013, 'Tree genera classification with geometric features from high-density airborne LiDAR', *Canadian Journal of Remote Sensing*, vol. 39, no. S1, pp. S73-S85.

Korpela I, Ørka H, Maltamo M, Tokola T & Hyyppä J 2010, 'Tree Species Classification Using Airborne LiDAR – Effects of Stand and Tree Parameters, Downsizing of Training Set, Intensity Normalization, and Sensor Type', *Silva Fennica*, vol. 44, no. 2, pp. 319-339.

Liaw A & Wiener M 2002, 'Classification and Regression by randomForest', *R News*, vol. 2, no. 3, pp. 18-22.

Li J, Hu B & Noland T 2013, 'Classification of tree species based on structural features derived from high density LiDAR data', *Agricultural and Forest Meteorology*, vol. 171-172, pp. 104-114.

Lombard L, Ismail R & Poona N 2017, 'Modelling forest canopy gaps using LiDAR-derived variables', *Geocarto International*, DOI: 10,1080/10106049,2017,1377775.

Lucas R, Bunting P, Paterson M & Chrisholm L 2008, 'Classification of Australian forest communities using aerial photography, CASI and HyMap data', *Remote Sensing of Environment*, vol. 112, pp. 2088-2103.

Macfarlane D 2006, 'State of the environment report', Sappi Forests, KwaZulu-Natal.

Mallinis G, Koutsias N, Tsakiri-Strati M & Karteris M 2008, 'Object-based classification using Quickbird imagery for delineating forest vegetation polygons in a Mediterranean test site', *ISPRS Journal of Photogrammetry & Remote Sensing*, vol. 63, pp. 237-250.

Maltamo M, Næsset E & Vauhkonen J 2014, *Forestry Applications of Airborne Laser Scanning: Concepts and Case Studies*, Springer, Dordrecht.

Mhangara P & Odindi J 2013, 'Potential of texture-based classification in urban landscapes using multispectral aerial photos', *South African Journal of Science*, vol. 109, no. 3/4, pp. 1-8.

Moffiet T, Mengersen K, Witte C, King R & Denham R 2005, 'Airborne laser scanning: Exploratory data analysis indicates potential variables for classification of individual trees or forest stands according to species', *ISPRS Journal of Photogrammetry & Remote Sensing*, vol. 59, pp. 289-309.

Mulyani M & Jepson P 2017, 'Does the 'One Map Initiative' Represent a New Path for Forest Mapping in Indonesia? Assessing the Contribution of the REDD+ Initiative in Effecting Forest Governance Reform', *Forests*, vol. 8.

Ørka H, Næsset E & Bollandsås O 2009, 'Classifying species of individual trees by intensity and structure features derived from airborne laser scanner data', *Remote Sensing of Environment*, vol. 113, pp. 1163-1174.

Peerbhay K, Mutanga O & Ismail R 2013, 'Commercial tree species discrimination using airborne AISA Eagle hyperspectral imagery and partial least squares discriminant analysis (PLS-DA) in KwaZulu-Natal, South Africa', *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 79, pp. 19-28.

Peerbhay K, Mutanga O & Ismail R 2014, 'Investigating the Capability of Few Strategically Placed Worldview-2 Multispectral Bands to Discriminate Forest Species in KwaZulu-Natal, South Africa', *IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing*, vol. 7, no. 1, pp. 307-316.

Puttonen E, Litkey P & Hyyppä J 2010, 'Individual Tree Species Classification by Illuminated-Shaded Area Separation', *Remote Sensing*, vol. 2, pp. 19-35.

Qin Y, Xiao X, Wang J, Dong J, Ewing K, Hoagland B, Hough D, Fagin T, Zou Z, Geissler G, Xian G & Loveland T 2016, 'Mapping Annual Forest Cover in Sub-Humid and Semi-Arid Regions through Analysis of Landsat and PALSAR Imagery', *Remote Sensing*, vol. 8.

Rahman M & Saha S 2008, 'Multi-resolution Segmentation for Object-based Classification and Accuracy Assessment of Land Use/Land Cover Classification using Remotely Sensed Data', *Journal of the Indian Society of Remote Sensing*, vol. 36, pp. 189-201.

R Development Core Team 2017, *R: A Language and Environment for Statistical Computing [online]*, Vienna, Austria, viewed 8 June 2017, <https://www,r-project,org/>.

Shang X & Chrisholm L 2014, ‘Classification of Australian Native Forest Species Using Hyperspectral Remote Sensing and Machine-Learning Classification Algorithms’, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 7, no. 6, pp. 2481-2489.

Trimble 2016, *eCognition Trial Software [online]*, viewed 21 October 2016, <http://www,ecognition,com/free-trial>.

Waser L, Fischer C, Wang Z & Ginzler C 2015, ‘Wall-to-Wall Forest Mapping Based on Digital Surface Models from Image-Based Point Clouds and a NFI Forest Definition’, *Forests*, vol. 6, pp. 4510-4528.

Vaughn N, Moskal L & Turnblom E 2012, ‘Tree Species Detection Accuracies Using Discrete Point Lidar and Airborne Waveform Lidar’, *Remote Sensing*, vol. 4, pp. 377-403.

Vauhkonen J, Tokola T, Packalén & Maltamo M 2009, ‘Identification of Scandinavian Commercial Species of Individual Trees from Airborne Laser Scanning Data Using Alpha Shape Metrics’, *Forest Science*, vol. 55, no. 1, pp. 37-47.

Xie Y, Sha Z & Yu M 2008, ‘Remote sensing imagery in vegetation mapping: a review’, *Journal of Plant Ecology*, vol. 1, no. 1, pp. 9-23.

Yu X, Litkey P, Hyyppä J, Holopainen M & Vastaranta M 2014, ‘Assessment of Low Density Full-Waveform Airborne Laser Scanning for Individual Tree Detection and Tree Species Classification’, *Forests*, vol. 5, pp. 1011-1031.

Yunfei B, Guoping L, Chunxiang C, Xiaowen L, Hao Z, Qisheng H, Linyan B & Chaoyi C 2008, ‘Classification of LIDAR point cloud and generation of DTM from LIDAR height and intensity data in forested area’, Proceedings of IAPRS XXXVII, Beijing, China: The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences.