SPOT-5 MULTISPECTRAL IMAGE FOR PINE PLANTATION STRUCTURE MAPPING

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KEY WORDS: SPOT-5, Pine Plantation, Texture, Estimation, Structure Mapping

ABSTRACT: The huge extents of the softwood plantations in Australia's national forests (about 1,020,000 hectare in 2009) require continuous silviculture operations. Consequently a reliable and continuous quantification of the plantation structure is needed to sustainably manage them. Remote sensing data is considered as a cost-effective and efficient tool for this task and several remotely sensed datasets have been examined for this purpose, including SPOT-5 data. In this study, different derivatives of SPOT-5 multispectral images including spectral and textural indices were examined for estimating inventory parameters of a *Pinus radiata* plantation in New South Wales, Australia. The spectral derivatives included individual bands, band ratios, principal components (PCs), and 19 vegetation indices extracted for 61 plots collected randomly over the study area. Grey level co-occurrence matrix (GLCM) indices were also calculated for individual bands, band ratios and PCs, for different window sizes and orientations. Stepwise multiple-linear regression was used to examine the relationship between each spectral and textural attributes and structural parameters including mean height, mean diameter at height breast (DBH), stand volume, basal area, and stocking. The results showed textural indices perform better than spectral attributes for estimating the structural parameters of the plantation. Moreover, adding spectral derivatives to the textural indices did not improve the results derived from the models achieved from textural indices. Among different structural parameters, mean height and mean DBH were estimated with errors of 13% and 17.1% which are better than the acceptable error of forest sampling, while the errors of estimation for other structural parameters are more than 20%.

1. INTRODUCTION

Sustainable management of commercial pine plantation requires updated and precise information about the vertical and horizontal distribution of the trees and their biophysical and structural characteristics (Shamsoddini, 2012). The conventional field based methods of the forest inventory for measuring tree parameters, such as height and DBH, usually take enormous amount of time and money (Martin et al., 1998; Hyyppa et al., 2000) and large scales field based inventories are impossible (Ustin and Xiao, 2001). In Australia, *Pinus radiata* covers more than 75% of 1.02 million hectare pine plantation (Stone et al., 2012). Applications of remotely sensed data as a reliable alternative to conventional forest inventory to measure the structural parameters of this huge plantation are inevitable. Although, numerous studies have been conducted for mapping the structure of the forests and plantations using optical remotely sensed data (Kayitakire et al., 2006; Wolter et.al, 2009), radar data (Neumann et al., 2010), and lidar data (Dean et al., 2009), optical data are considered as most suitable for this task due to their availability, cost and processing time required.

Different types of measures can be determined for biophysical and inventory parameter estimation from optical data acquired in different spectral bands, including vegetation indices (VIs), spectral derivatives and textural information. While some studies have shown the suitability of spectral derivatives, including VIs, for retrieval of biomass and

productivity of the forests (Goward and Dye, 1987), other studies have demonstrated limitations of VIs for estimating structural parameters, especially stand volume (Trotter et al., 1997; Kilpelainen and Tokola, 1999). It is believed that textural information extracted from the images can perform effectively for forest parameterization since they can efficiently reveal the spatial variation of the forest stands (Hyyppa et al., 2000). Different methods, e.g. semi-variogram and GLCM, have been used for extracting textural information from the images. There are difficulties in generating semi-variograms especially for large areas, which cause this method to be impractical (Kayitakire et al., 2006), and therefore GLCM has been applied in many forest studies. The extracted spectral and textural information are then modelled using typically regression and multiple regression models, neural network, classification methods and empirical methods (Hyyppa et al., 2000; Cohen et al., 2003; Ingram et al., 2005; Labrecque et al., 2006; Shamsoddini et al.,2011). Some of these methods such as neural networks require sufficient samples to be separated into training, validation and test datasets (Shamsoddini et al., 2011). As it is time consuming and expensive to collect large numbers of plots over a forested area for these three separate datasets, multiple-linear regression is commonly applied for the cases in which a limited number of plots is available. Moreover, the implementation of this method is easier.
According to above considerations, in this study, the SPOT-5 multispectral imagery acquired over a *Pinus radiata* plantation, in Australia has been utilized to quantify different structural parameters in this plantation including mean height, mean DBH, stocking, basal area and stand volume. This study aims to:

- Examine the VIs, spectral derivatives and GLCM attributes derived from SPOT-5 multispectral image for estimating structural parameters.
- Assess the effect of different strata on the results of the structural parameter estimations.
- Identify the structural parameters which are estimated better than others using SPOT-5 data.

In order to reach these aims, in addition to VIs, band reflectance, band ratios and PCs, and their textural information were calculated, and multiple-linear regression was used to model the relationship between these data and each inventory parameter of the pine plantation.

2. STUDY AREA AND DATA

The study area is a 5000 ha *Pinus radiata* plantation within 35º 23' 35'' S to 35º 29' 58'' latitude, and 147º 58' 48''E to 148º 04' 02'' E longitude, in NSW, Australia, as shown by the false colour composite SPOT-5 multispectral image in Figure 1.

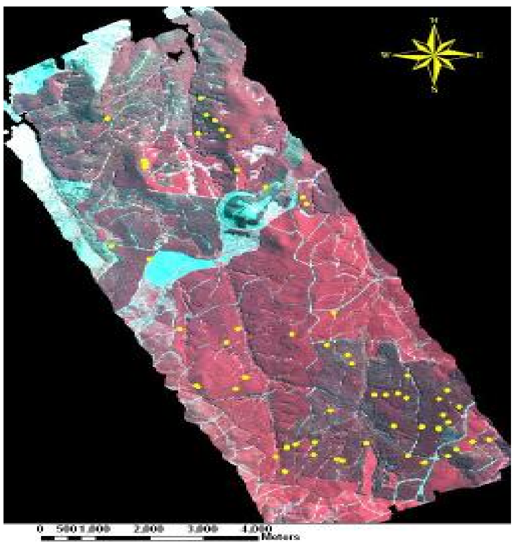


Figure 1. The study area on the of SPOT 5 false colour composite (red band=NIR, green band=red and blue band=green). The yellow circles represent 61 field collected plots.

The annual average rainfall of this area is 1200 mm and its average elevation is 750 m above mean sea level. The terrain varies in slope from 0 to more than 30 degrees. The site is an active commercially plantation on which the silviculture operations such as thinning are applied in different sections. The plantation's spatial characteristics depend on the age of the stands and thinning history, and therefore the tree density varies depending on the thinning condition. Stem density commences at almost 1000 stems per hectare for unthinned sections, which reduces to 450-500 and 200-250 for the first thinning and second thinning classes, respectively. Moreover, the age of trees ranges from less than 10 years for the re-growth areas to more than 30 years.

Forests NSW and the Department of Industry and Investment (IINSW) collected 61 stratified random plots aimed at covering three strata including: three thinning conditions, unthinned, first thinning, and second thinning; three age classes, 10-20 years, 21-30 years and more than 30 years; and three slope classes, less than 10 degrees, 10 to 20 degrees and more than 20 degrees, over the study area in 2008. The size of the collected plots was variable, ranging from 7 to 20 m radius, as the aim of the field data collection was to have at least 15 trees per plot. A laser theodolite (Leica 2 second T1100 total station) and a differential global positioning system (dGPS) were utilized to position each tree and the centre of each plot. Nearly 978 trees were surveyed for height and DBH. In order to reduce the error of the measurement the tree heights were measured twice using a Vertex hypsometer. The stem volume of each measured tree was calculated using an in-house equation using height and DBH (Bi, personal communication, 2011). Using the field and calculated data, five structural parameters including mean height (m), mean DBH (cm), stocking (tree/ha), basal area (m^2/ha), and stand volume (m^3/ha) were calculated for each plot. More information about the statistics of the structural parameters calculated for this study can be found in Shamsoddini (2012).

Multispectral SPOT-5 data including green, red, near infrared (NIR) and shortwave infrared (SWIR) bands which were acquired on 5 April 2008 were used for this study. The orthorectified SPOT-5 data was provided with spatial resolution of 10 m (SWIR image whose pixel size is originally 20 m was resampled to 10 m). The false color composite of SPOT-5 multispectral image of the study area is shown in figure 1.

3. METHODOLOGY

The methodology is divided into three different steps including geometric and atmospheric corrections, attribute extraction and modelling.

In order to increase the geometric accuracy of the image, the orthorectified SPOT-5 multispectral image was registered to an orthorectified WorldView-2 image using 50 ground control points and a first order polynomial function which resulted in a registration accuracy of better than half pixel. After geometric correction, the image was tested to indicate whether it required suppression of the topographic effects prior to the atmospheric correction. For this purpose, the digital terrain model (DTM) derived originally from lidar data acquire over the area with 1 m resolution, was resampled to 10 m and the cosine of incident angle, cos (i), (Riano et al., 2003) was calculated using the slope and aspect maps derived from this DTM. Moreover, SPOT-5 digital number (DN) values were converted to top of atmosphere spectral radiance and its path radiance, which is considered as 1% of surface reflectance for dark objects (Song et al., 2001), was removed prior to the topographic effect correction. The examination of the relationship between radiance bands of SPOT-5 and cos (i) indicated that the implementation of topographic effect suppression is not necessary as they are not significantly correlated. Finally, dark object subtraction (DOS3) was applied on SPOT-5 radiance bands to remove the effect of the atmosphere and convert the DN values to reflectance.

Spectral information comprising band reflectance, band ratios, principal components (PCs) were calculated using SPOT-5 multispectral data, as well as 19 VIs shown in table 1. The aim of the selection of these VIs was to cover a variety of VIs which are calculated using the four bands of SPOT-5. GLCM was used to extract the textural information of the image, based on the 11 indices as used in Shamsoddini et al. (2011) and Shamsoddini (2012) for bands, band ratios and PCs. These GLCM indices were calculated for four window sizes, 3×3 to 9×9, and four orientations, 0°, 45°, 90° and 135°.

After extraction of the spectral and textural attributes, a stepwise multiple-linear regression was applied to model the relationship between these attributes and structural parameters of the pine plantation. In order to avoid multicollinearity and over-fitting, the conditions which are given in Shamsoddini (2012) were considered in this study and models which did not meet these conditions were excluded. Moreover, leave-one-out cross validation (Efron and Tibshirani, 1993) was used for validating the selected models. Correlation of determination (R^2) and standard error of the estimation (SEE) were calculated for the predicting models to reveal their fitness and accuracy. Finally, two types of statistical t-test, namely paired samples t-test and independent samples t-test were applied on the residuals of the predicted and measured structural parameters to compare the efficiency of the models and to examine the effect of the three strata on the accuracy of the predictions.

Vegetation indices	Reference
Difference vegetation index (DVI)	Richardson and Weigand (1979)
Weighted difference vegetation index (WDVI)	Clevers (1989)
Normalized difference vegetation index (NDVI)	Rouse et al. (1973)
Green NDVI (GNDVI)	Rouse et al. (1973)
Soil-adjusted vegetation index (SAVI)	Huete (1988)
Optimized soil-adjusted vegetation index (OSAVI)	Rondeaux et al. (1996)
Transformed SAVI (TSAVI)	Baret et al. (1989)
Modified SAVI (MSAVI)	Qi et al. (1994)
Perpendicular vegetation index (PVI)	Richardson and Weigand (1979)
Modified chlorophyll absorption in reflectance index2 (MCARI2)	Haboudane et al. (2004)
Modified triangular vegetation index2 (MTVI2)	Haboudane et al. (2004)
θ NDVI	Unsalan and Boyer (2004)
θ SAVI	Zhangyan et al. (2006)
Global environment monitoring index (GEMI)	Pinty and Verstraete (1991)
Infrared percentage vegetation index (IPVI)	Crippen (1990)
Reflectance ratio or ratio vegetation index(RVI)	Pearson and Miller (1972)
Modified simple ratio(MSR)	Chen et al. (1996)
Triangular vegetation index (TVI)	Broge and Leblanc (2000)
shortwave infrared to visible ratio (SVR)	Wolter et al., (2008); Wolter et al., 2009

Table1. VIs utilized in this study

4. RESULTS AND DISCUSSION

The performance in estimating structural parameters following the stepwise multiple-linear regression, applied on different spectral and textural attributes extracted from SPOT-5 multispectral image, will be assessed in the following sections.

4.1 Performance of SPOT-5 spectral derivatives

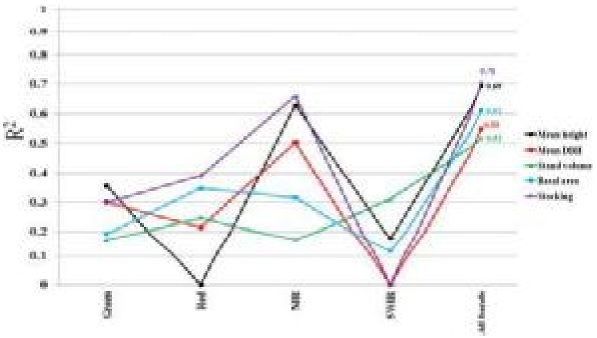
Among the spectral derivatives of SPOT-5 studied, the performance of all PCs is better than the others for explaining the variation of different structural parameters, except for the estimation of mean DBH where VIs provided better estimation compared to all PCs. The variability of stocking and mean height with relatively low values of 38% and 37% respectively, are explained better than the other structural parameters. Also, PC4 is more important than the other PCs derived from SPOT-5 data since it was selected more than the other PCs for estimating structural parameters. VIs provided better estimation of mean DBH although with relatively low R^2 of 0.33 and SEE of 8.0 cm among the spectral derivatives. Also, WDVI and SVR are the most useful vegetation indices as they are selected as predictors by the models more than other VIs; however, GEMI and MSR are also important as they are the only predictors for estimating stocking and mean DBH. According to table 2, including all spectral derivatives in the multiple-linear regression can increase the accuracy of the structural parameter estimations, except for mean DBH.

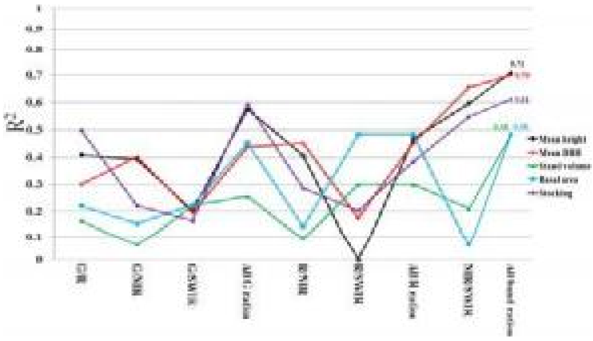
Structural Parameter	R^2	R^2_{adj}	SEE	p-level	Attribute and intercept	B	Std.err. of B	p-level	Tol	VIF	EV	CI
Height (m)	0.399	0.367	4.57	0.000	Intercept	55.17	6.651	0.000				
					WDVI	-0.859	0.148	0.000	0.46	2.20	0.35	3.23
					PC3	14.12	3.514	0.000	0.31	3.26	0.03	10.5
					Red	-1.751	0.835	0.041	0.52	1.91	0.01	25.8
Mean DBH (cm)	0.329	0.318	7.997	0.000	Intercept	51.034	4.021	0.000				
					MSR	-17.65	3.282	0.000	1.00	1.00	0.03	7.72
Stand Volume (m^3/ha)	0.301	0.277	109.4	0.000	Intercept	451.24	80.40	0.000				
					PC4	363.71	103.92	0.001	0.97	1.04	0.34	2.79
					Red	-42.14	14.73	0.006	0.97	1.04	0.02	12.7
Basal area (m^2/ha)	0.256	0.230	9.48	0.000	Intercept	10.159	6.776	0.139				
					PC4	45.07	10.25	0.000	0.75	1.34	0.39	2.59
					NIR/SW	1.356	0.472	0.006	0.75	1.34	0.02	11.9
Stocking (tree/ha)	0.377	0.355	298	0.000	Intercept	77.94	121.89	0.525				
					GEMI	6.932	1.183	0.000	0.70	1.43	0.52	2.15
					PC3	-384.1	152.01	0.014	0.70	1.43	0.06	6.37

Table 2. Predictive model results using all spectral derivatives of SPOT-5 multispectral data

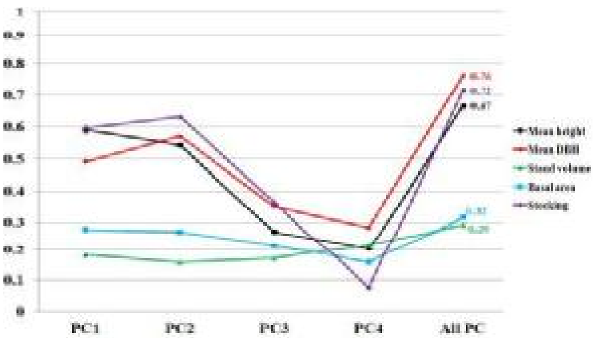
4.2 Performance of SPOT-5 textural attributes

The results of including all textural attributes, calculated for four bands of SPOT-5 multispectral image, to develop the models are presented in Figure 3a, which reveals R^2 derived for textural attributes of each band and all bands. The best performance for estimation of mean height, mean DBH and stocking with R^2 of 0.63, 0.50 and 0.66 and SEEs of 3.7 m, 7 cm and 226 tree/ha belongs to the textural attributes derived from NIR band. Also, textural attributes of red and SWIR bands provide the best estimations of basal area and stand volume, respectively, although with relatively low R^2 of 0.35 and 0.31 and SEEs of 8.9 m^2/ha and 109.6 m^3/ha. Finally, using the textural attributes of all bands can improve the accuracy of the estimations derived from individual bands, especially for basal area and stand volume estimations, by 21% for these structural parameters.





(a) **(b)**



(c)

Figure 3. (a), (b), and (c) are the performance of the textural attributes derived for bands, band ratios, and PCs of SPOT-5 for estimating of pine plantation structure parameters

Figure 3b reveals the R^2 results of the structural parameter estimation derived from band ratios of SPOT-5 data. Among 6 band ratios of SPOT-5 multispectral image, the textural attributes derived from the band ratio of NIR to SWIR perform more efficiently than the other band ratios for estimating mean height, mean DBH and stocking with R^2 of 0.60, 0.66 and 0.55 and SEEs of 3.8 m, 5.9 cm and 256 tree/ha, respectively. In addition, the textural attributes derived from the combination of SWIR band with red band were able to estimate basal area and stand volume with R^2 of 0.48 and 0.30 and SEEs of 8.1 m^2/ha and 109.6 m^3/ha which are better than that derived using the other band ratios. Moreover, this figure indicates that the variability of the structural parameters, especially stand volume and mean height are explained more efficiently (18% and 11% improvement, respectively) when all band ratios are used together for developing multiple-linear regression models. According to the figure 3c, which shows the results of R^2 for estimating structural parameters using textural attributes of PCs, the best results of mean height, mean DBH, stocking and basal area with R^2 of 0.54, 0.57, 0.63, and 0.27 were derived from textural attributes of PC2. Moreover, the results of structural parameter estimation are improved by using the textural indices of all PCs together.

Among different bands of SPOT-5, the best results of mean height, mean DBH and stocking were derived from the NIR band. The usefulness of the NIR band for structural parameter estimation was confirmed by Nichol and Sarker (2011) who used SPOT-5 and AVNIR/ALOS data with similar spatial resolution for biomass estimation. Also, the combination of SWIR with red and NIR bands as ratios provides better results for structural parameter estimation compared to the other band ratios. The usefulness of combinations of SWIR with other bands especially NIR for estimating different structural parameters such as basal area, tree density, and mean height has been confirmed by several studies on coniferous forests (Wolter et al., 2009). Among different spectral derivatives of SPOT-5 data, PCs perform better than the other spectral derivatives, except for mean DBH which is derived more accurately using VIs. The models derived from PCs are not able to explain the variation of the structural parameters better than 35%. Among the different VIs used in this study, it was shown that WDVI and SVR are more useful than the other VIs for mean height, stand volume and basal area. The models derived from all spectral derivatives of SPOT-5 perform better than PCs-based models.

A comparison of the results shown in figure 3 indicates that the best results of mean height estimation is derived from all band ratios while the mean DBH and stocking are estimated better using all PCs with SEE of 5.0 cm and 207 tree/ha, respectively. Also, the models derived from textural attributes of all bands provided the best estimations of basal area and stand volume with SEEs of 7.3 m^2/ha and 94.2 m^3/ha. Finally, the best estimation of structural parameters was achieved using textural attributes of all bands, all band ratios, and all PCs as shown in table 3. According to the attribute and intercept column of this table, the textural attributes derived from band ratios, especially those derived from the combination of SWIR with other bands, were selected more than those derived from bands and PCs.

4.3 Final Models, Validation and Strata Effect

Tests to determine the feasibility of using spectral derivatives and textural indices together for estimating structural parameters by multiple-linear regression indicated that there is no improvement compared with the models derived from textural attributes only. Consequently, the models given in table 3 were selected as the final models for estimating structural parameters of pine plantation using SPOT-5 multispectral image. To compare the performance of these final models with those developed using all spectral derivatives and VIs, paired-samples t-tests were applied to the residuals of the validated results of these modes. Table 4 shows the results of the leave-one-out cross validation used for the different models of structural parameter estimation. The paired-samples t-test was applied on the absolute values of the residuals of the predicted structural parameters.

According to these results, the models derived from textural attributes of SPOT-5 data perform significantly better, as shown in bold and italic text in table 4, than those derived from VIs and all spectral derivatives. Also, integration of VIs and the other spectral derivatives do not increase the accuracy of the structural parameter estimations significantly, except for stocking. The spatial relationships between individual trees and stand structure are modelled by textural analysis (Wulder et al., 1998) and therefore it provides valuable information about the spatial variation of forests. Moreover, several studies have shown that textural information (e.g. GLCM) perform more efficiently than spectral information such as VIs for structural parameter estimation (Trotter et al., 1997; Kilpelainen and Tokola, 1999). Foody et al. (2001) suggested that VIs do not perform efficiently for quantifying structural parameters due to following reasons: (i) the asymptotic relationship between vegetation indices and biomass parameters can lead to inaccurate evaluation of high biomass forests; (ii) the vegetation indices are environmentally dependent; and (iii) they often do not utilize all spectral data together.

The R^2 of mean height, mean DBH and stocking was 0.75, 0.77 and 0.74 respectively for the final models of SPOT-5. Also the SPOT-5 final models were able to explain 58% and 60% variations of basal area and stand volume, respectively. The error of estimation derived from leave-one-out cross validation for structural parameters showed that the mean height is predicted more precisely than other forest structure parameters with 13% error using SPOT-5 models. Also, mean DBH was estimated by SPOT-5 model with 17.1% error which is also similar to the acceptable error of field based forest inventory which is 15% to 20% (Holmgren and Thuresson, 1998), while the error of basal area, stand volume and stocking estimations was worse. Finally, the performance of SPOT-5 models in this study was better than that described by Hyyppa et al. (2000) who used SPOT XS data with 20 m spatial resolution for estimating basal area and stand volume, and Wolter et al. (2008) who used Landsat TM and ETM+ for estimating basal area over coniferous forests.

The effects of the three different strata, namely thinning, age with two classes, less than 20 years old and more than 20 years old, and slope, on the accuracy, and overestimation or underestimation of the results of final models derived from SPOT-5 textural attributes, were examined using an independent samples t-test. To determine the effect of strata on the accuracy of the predictions, the absolute values of residuals were used, and for investigating the effect of the strata on underestimation and overestimation of the predictions, the actual values of residuals were considered. The results of t-test on the absolute and actual values of residuals indicate that:

Structural Parameter	R^2	R^2_{adj}	SEE	p-level	Attribute and intercept	B	Std.err. of B	p-level	Tol	VIF	EV	CI
Height (m)	0.826	0.791	2.6	0.000	Intercept	27.04	2.736	0.000				
					CORd135w9B3-4	-24.54	4.713	0.000	0.21	4.88	1.15	2.66
					CORd135w5B3-4	22.60	4.561	0.000	0.25	3.97	0.76	3.27
					CORd135w7B3	-14.34	2.443	0.000	0.65	1.54	0.35	4.79
					MEd45w3P4	18.00	2.742	0.000	0.83	1.21	0.22	6.13
					MPd0w9B1	-39.12	8.474	0.000	0.71	1.42	0.17	6.86
					ASMd0w3B4	16.66	5.044	0.002	0.64	1.57	0.09	9.40
					CORd45w3B1-2	-22.86	5.831	0.000	0.28	3.64	0.06	11.8
					CORd45w5B1-2	14.09	5.030	0.007	0.24	4.22	0.05	12.6
					CORd0w7B2-3	-8.74	2.474	0.001	0.75	1.34	0.03	16.3
					CORd0w5B2	5.71	2.453	0.024	0.82	1.23	0.01	26.5
Mean DBH (cm)	0.844	0.813	4.2	0.000	Intercept	42.01	3.587	0.000				
					MEd45w3P2	2.10	0.304	0.000	0.73	1.37	0.96	2.91
					CORd0w9P2	-28.59	6.01	0.000	0.37	2.71	0.71	3.39
					DISSd45w3P1	4.16	0.688	0.000	0.83	1.21	0.43	4.36
					CORd135w9B3-4	-43.17	6.953	0.000	0.24	4.16	0.32	5.08
					CORd135w5B3-4	45.53	7.667	0.000	0.23	4.40	0.17	6.83
					CORd135w5P1	-23.92	4.856	0.000	0.43	2.31	0.11	8.54
					CONd135w3B1-2	-239.3	92.93	0.013	0.78	1.28	0.09	9.70
					CORd0w5B2-4	12.20	3.991	0.004	0.85	1.18	0.05	12.3
					CORd135w9B2-3	19.21	5.766	0.002	0.45	2.22	0.03	18.2
					CORd0w3P1	9.75	3.769	0.013	0.64	1.58	0.02	22.6
Stand Volume (m^3/ha)	0.712	0.661	74.9	0.000	Intercept	553.05	90.45	0.000				
					CORd90w9B3-4	-452.2	70.55	0.000	0.64	1.56	1.07	2.55
					MPd0w5B2	788.77	131.88	0.000	0.66	1.53	0.83	2.89
					CORd90w3B2-3	333.94	71.34	0.000	0.65	1.54	0.68	3.20
					CORd0w5P4	691.73	248.84	0.008	0.84	1.19	0.18	6.30
					CORd135w5B2-4	316.92	72.02	0.000	0.71	1.40	0.13	7.34
					CORd0w9P1	-582.9	100.97	0.000	0.46	2.18	0.07	10.3
					CORd0w5B2-3	315.55	82.92	0.000	0.54	1.86	0.04	13.5
					CONd0w9B2-3	1.98	0.838	0.022	0.86	1.16	0.03	15.8
					MPd0w9B2-3	-4686	2096.2	0.030	0.82	1.23	0.01	29.9
Basal area (m^2/ha)	0.717	0.661	6.3	0.000	Intercept	5.81	3.285	0.360				
					ASMd135w9B2-4	1080.2	176.30	0.000	0.57	1.75	1.15	2.50
					CORd135w5B2-4	19.30	5.720	0.001	0.80	1.25	0.97	2.71
					CORd45w5B2	29.88	7.125	0.000	0.70	1.43	0.72	3.15
					MEd45w3P4	50.30	9.148	0.000	0.43	2.33	0.38	4.35
					MPd90w9B1-2	-270.9	57.32	0.000	0.59	1.70	0.25	5.34
					MEd45w3P2	-2.66	0.617	0.000	0.40	2.51	0.15	6.96
					STd90w9B2-4	6.86	2.266	0.004	0.72	1.39	0.09	8.76
					CORd45w3B2-4	-19.17	8.573	0.030	0.88	1.14	0.08	9.79
					VARd45w3P4	135.00	56.77	0.021	0.82	1.23	0.05	12.3
					CONd0w9B3	-0.314	0.141	0.031	0.65	1.55	0.01	22.9
Stocking (tree/ha)	0.861	0.833	152	0.000	Intercept	623.92	162.26	0.000				
					MEd45w3P2	-71.37	10.454	0.000	0.81	1.24	0.96	2.84
					CORd45w9B3	819.07	112.69	0.000	0.69	1.45	0.77	3.16
					CONd135w9B2	76.92	10.26	0.000	0.36	2.76	0.64	3.48
					STd135w9B4	-1087	170.32	0.000	0.28	3.62	0.46	4.12
					MPd90w9B3	-6246	2089.3	0.004	0.77	1.30	0.16	6.92
					CORd90w3B1	788.63	135.83	0.000	0.63	1.58	0.12	8.08
					CORd90w5B1-4	-502.5	144.47	0.001	0.60	1.66	0.07	10.7
					CORd0w9B1-4	649.06	162.21	0.000	0.61	1.64	0.06	11.5
					CORd45w3P4	642.23	212.01	0.004	0.81	1.23	0.05	12.8
					MPd0w5B2	878.60	265.48	0.002	0.66	1.51	0.01	26.6

Note: in this table the code to the GLCM attribute is shown by xx dx wx yx, where xx presents the abbreviation name of attributes. COR, ME, MP, CON, DISS, ST, VAR and ASM are abbreviations of *correlation*, *mean*, *maximum probability*, *contrast*, *dissimilarity*, *standard deviation*, *angular second moment* and *angular second moment*, respectively. dx and wx show the orientation and window size, respectively and yx represents PC number if y is P; otherwise it shows the number of band or band ratio.

Table 3. Results of the models derived using textural attributes of all bands, band ratios and PCs of SPOT-5

- The slope classes do not affect the accuracy of estimation of structural parameters calculated using the final models of SPOT-5. Likewise, these results were not underestimated or overestimated due to the effect of slope classes.
- Mean height is the only structural parameter whose estimation accuracy is affected by the thinning condition since the accuracy of estimation significantly increases when the thinning process progresses from unthinned to second thinning classes. Moreover, while mean height and mean DBH are underestimated for the plots pertaining to the second thinning class, stocking is significantly overestimated for these plots.
- The age classes do not affect the estimation accuracy of the structural parameters, but mean height and basal area are underestimated for the plots which contain trees more than 20 years old, while these parameters are overestimated for the other plots with younger trees.

Actually, different age classes did affect the average value of structural parameters in the field data. For example, the average values of mean height, mean DBH, stand volume and basal area for the plots more than 20 years old are higher than those less than 20 years old in the field data, whereas the average value of stocking decreases for the plots more than 20 years old due to the thinning operations. Accordingly, it seems that for SPOT-5 data, any structural parameter is underestimated in plots which have a high average value of the parameter, whereas overestimation occurs in plots with a low average value of the parameter.

Table 4. The validation results of the final models derived from SPOT-5 data

Structural parameter	Models	R^2	SEE	Error of estimation (%)
Mean height (m)	VIs	0.22	5.18	21.6
	All spectral derivatives	0.40	4.88	20.3
	Textural indices	***0.75***	***3.13***	***13.0***
Mean DBH (cm)	VIs	0.29	8.25	27.4
	All spectral derivatives	0.29	8.25	27.4
	Textural indices	***0.77***	***5.14***	***17.1***
Stand volume (m^3/ha)	VIs	0.13	122.9	41.5
	All spectral derivatives	0.30	114.3	38.6
	Textural indices	***0.60***	***89.3***	***30.2***
Basal area (m^2/ha)	VIs	0.02	10.84	32.2
	All spectral derivatives	0.19	9.91	29.4
	Textural indices	***0.58***	***7.79***	***23.1***
Stocking (tree/ha)	VIs	0.31	328	55.1
	All spectral derivatives	0.39	296	49.7
	Textural indices	***0.74***	***222***	***37.3***

5. CONCLUSION

According to the examination of this study on SPOT-5 multispectral data for estimating structural parameters of the pine plantation, the following conclusions are highlighted:

- Among different bands of SPOT-5 data, NIR (780-790 nm) band performs better than the other bands for mapping the structural parameters of the pine plantation.
- The combination of SWIR with NIR and red band can lead to some improvement in the results of mean DBH and stand volume.
- Textural attributes perform significantly better than spectral information including VIs for estimating structural parameters of the pine plantation for SPOT-5.
- Mean height and mean DBH were estimated more accurately than stocking, basal area and stand volume whose errors of estimation were more than 20%.
- The accuracy of predicting mean height is significantly affected by thinning conditions and is higher for the second thinning class where the trees are expected to be taller than the trees of the other thinning classes.

- The effect of age on the average values of the structural parameters leads to the underestimation of the structural parameters for the plots with older trees and overestimation of the structural parameters for the plots with younger trees.

Although, multiple-linear regression provides promising results for some of structural parameters, more advanced modelling techniques such as neural network and support vector regression should also be undertaken for mapping the structural parameters of pine plantations. Such tests should indicate whether the estimation accuracy of the structural parameters, such as basal area and stand volume, can be improved.

Acknowledgement

Data utilized in this study was kindly supplied by the New South Wales Department of Industry and Investment (IINSW) and Forests NSW (FNSW), with partial sponsorship from the Forest and Wood Products Australia (FWPA). Moreover, the authors wish to express appreciation to SPOT Imaging Services, NSW for providing SPOT-5 image.

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