Chapter 42
Quantify Forest Stand Volume Using SPOT 5 Satellite Image

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Abstract Stand volume is one of important attributes in forest management and quantification of forest resource value. This studies tested solutions to estimate forest stand volume for the large area using SPOT 5 data and field data. Firstly, the forests were stratified into four strata using maximum likelihood supervised classification methods based on SPOT 5 and field data. A set of 111 sample plots was distributed in these four forest strata, which represented four disturbed (by humans) forests under different levels in the tropical forest in Tuy Duc district of Dak Nong Province. Within the sample plots, DBH and tree height were measured to calculate stand volume using equation of stand volume from the previous study. The method of kNN (k-nearest neighbour) was applied to estimate the stand volume using SPOT 5 and field data. The estimates were tested on SPOT 5 bands, normalized difference vegetation index (NDVI), and combination of SPOT 5 bands and NDVI for the whole area and for each forest stratum. Quality of the predictions was assessed using leave-one-out cross-validation method. The results indicated that the accuracy of estimate was significantly improved when applying for each stratum compared to the combined SPOT 5 and NDVI data. The lower errors were found in the forest strata of less disturbances than the heavy degraded stratum. Among the image data, the estimates were based on the NDVI giving the lower accuracy compared to other.

Keywords Remote sensing · Forest strata · Stand volume · K-nearest neighbour · RMSE

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1 Introduction

All decision-making demands information; in forestry, such information is collected by forest inventories that estimate forest characteristics over a defined area. The updated and quality of information will greatly contribute to the success of forest management (Nguyen, 2011). The mission of National Forest Inventory (NFI) is to produce and report timely and accurate estimates of forest resources (McRoberts & Tommp, 2007). The NFI monitoring in Vietnam has been conducted since the 1980s. As remote sensing data provide opportunity to estimate forest quality in vast areas with lower financial expenses compared to terrestrial inventory only, establishment of forest thematic maps using satellite image data is common application in forestry management (Nguyen, 2016). Accordingly, increasingly satellite imageries are considered as indispensable data in such national forest inventories in Vietnam. However, the main application is to map forest status under different level of disturbances (e.g. insignificant minor, medium, heavy impact). The forest attributes (e.g. volume) have been collected from the permanent system of sample plots distributed for the whole country. The inventory cycle is every 5 years; natural forests are always impacted by humans, and therefore, in addition to the inventory cycles a quick assessment should be done in timely and less costly manner. The advent of low-cost, widely available, remotely sensed data has been the basis for many of the important recent technological improvements. Remote sensing data have not only contributed to increasing speed, cost-efficiency, precision, and timeliness associated with inventories, but they have facilitated construction of maps of forest attributes with spatial resolutions and accuracies that were not feasible even a few years ago (McRoberts & Tommp, 2007); therefore, estimation of forest attributes using remotely sensed data is seen as a new potential for continuous management of natural resources (Mohammadia, Shataee, & Babanezhad, 2011). Since information about forest volumes is essential for forest management planning, large attempts have been given to estimate stand volume using different methods in order to improve estimation accuracy. Non-spatial modelling and spatial modelling are common methods to estimate the stand volume. A large quantity of literature has appeared to relate the estimation of stand volume using remote sensing data. Most of this literature has applied the regression method with linear or nonlinear regression (Awaya, Tsuyuki, Kodani, & Takao, 2004; Cohen, Maiersperger, Gower, & Turner, 2003; Fransson, Magnusson, & Holmgren, 2004; Rahman, 2004; Trotter, Dymond, & Goulding, 1997). Applying other regression types in forest attribute estimations and their spatial modelling using decision tree analysis such as regression tree has shown to be more useful compared to linear regression (Mohammadia et al., 2011). Geostatistics models have been given promising results (Meng, Cieszewski, & Madden, 2009; Nguyen, 2011; Tuominen, Holopainen, & Poso, 2006; Wallerman, Joyce, Vencatasawmy, & Olsson, 2002). Among the methods of forest attribute estimation, kNN is considered as a relatively simple and easy method to apply, becoming one of the most popular methods for conducting forest inventory using remote sensing (Meng et al., 2009). The kNN is known as a robust nonparametric method. It is used to estimate unknown values of data sets by means of similarity to reference data sets with known values (Scheuber, 2010) and to provide a very feasible tool for local to landscape level estimation (Gu et al., 2006); therefore, kNN has been applied widely in estimates of forest attributes since the first implementation of the multisource inventory based on the k-NN technique by the Finnish Forest Research Institute in 1990 (Tomppo, 2006).

The KNN method has two advantages in that it uses a nonparametric approach and allows for the use of robust to noisy training data. It is, therefore, becoming one of the most popular methods applied for forest inventory using large-area remote sensing data (Meng et al., 2009). kNN has been found as a useful tool for forest mapping over a large geographic area using a fine spatial resolution (Tokola, Pitkanen, Partinen, & Muinonen, 1996; Tomppo, Goulding, & Katila, 1999; Tomppo, Korhonen, Heikkinen, & Yli-Kojola, 2001; Holmström & Fransson, 2001; Tanaka et al., 2015; Lang, Gulbe, Traškovs, & Stepčenko, 2016). Although numerous studies of relationships between spectral responses and forest parameters have been conducted during the past several decades, conclusions about these relationships vary, depending on the characteristics of the study areas and the used data (Nguyen, 2011). Because of the complex forest stand structure and abundant vegetation species of tropical forests, the remote sensing spectral forest attributes relation is poorly understood (Lu, Mausel, Brondízio, & Moran, 2004). However, relatively less attention has been devoted to the moist tropical regions such as Asian forests; this might be due to difficulty in field data collection and complex biophysical environments. Meanwhile, a better understanding of forest stand parameters and spectral relationships is a prerequisite for effectively using appropriate image bands for developing spectral response-based estimation models (Lu et al., 2004).

2 Methodology

2.1 Study Area

The study was conducted in the district of Dak Nong Province. This forest site belongs to the Central Highlands of Vietnam. The study area is located between in $11^{0}59'$ to $12^{0}16'$ latitude North and 107°13′ to 107°28′ longitude East. The size of study area is about 500 square km (20 × 25 km). The forest is dominated by evergreen broad-leaved tropical natural forest but disturbed by humans over time at different levels. Many of valuable species trees have been selectively logged.

2.2 Data

Different data sources, including satellite image, digital data, and sample plots, were used under the study. The required satellite imagery product was SPOT 5 whose multi-spectral optical data was captured using the High Resolution Geometric

(HRG) instrument on board the satellite. The radiometric resolution is 256 digital levels, the spatial resolution is 10 m × 10 m and the images cover 60 km × 60 km. The SPOT 5 image was rectified using GCPs, and the elevation information was captured from a DEM created from an available 10 m contour line GIS shapefile. The SPOT image was projected to UTM 48 N, WGS84 to ensure compatibility between images and available digital data. A nearest neighbour resampling method was applied during this process with a pixel spacing of 10 m × 10 m in order to maintain the integrity of the pixel values. Because of the topographic effect of bright values of the images in some locations, some normalization algorithms were tested to remove this effect. The methods of Cosine, Minnaert method and C-correction were used to topographically correct the images (Blesius & Weirich, 2005; Jones, Settle, & Wyatt, 1988; Smith, Lin, & Ranson, 1980; Teillet, Guindon, & Goodenough, 1982). The C-correction was used since it presented the best one for topographic normalization for this area with the lowest determination of coefficient (R^2) (Nguyen, 2015).

A total of 111 sample plots with an approximate area of 0.1 ha with size similar to the SPOT 5 imagery pixel (10 x10 m) for each plot was sampled in the field. The stratified random sampling procedure was applied to assure that the sampling measurements captured all possible variability of forest conditions. Dense, moderate, open or/and very open forest structures were delineated during the field survey. Within the plots, the forest variables measured were breast height diameter (Dbh), tree height (H), tree density (N), and crown area (CA). Sample coordinates were recorded in the centroid position by GPSMap 60CSx. The standing volume equation was referred from previous research conducted by Nguyen (2011) for this area. This equation was then applied for all trees in all sample plots. For each plot, the mean forest parameters of sample plots and the 9-pixel means of SPOT 5 bands were calculated. The measured forest stand parameters were aggregated from 111 sample plots to represent forest stand conditions for forest classes. The standing volume equation was the following:

$$\begin{aligned} &Ln(V) = -10.0094 + 1.066 \times Ln(Dbh) + 1.933 \times Ln(H) \\ &With\, R^2 = 0.982, P < 0.05 \end{aligned} \tag{42.1}$$

where V is the stand volume; Dbh is the diameter at breast height; and H is the tree height.

2.3 Classifying SPOT 5 Image to Forest Strata

The stratification aims to divide forests into homogeneous units of one or a few specific indicators. Firstly, the forests were stratified using unsupervised classification algorithm of ISODATA (Iterative Self-Organization Data Analysis). Under forest-masked image, the forest was classified into maximum four classes as tested by Nguyen (2016) and considered as the first-phase sampling stage. Field sample plots were distributed on the classified image to measure forest attributes. In addition to the sample plots, field sample points were also taken based on prior knowledge to stratify the forest using supervised classification. The sample points and field data were distributed throughout the class to ensure the adequate representation of all the classes. The field data were chosen with respect to the size of the forest classes. One part of the field data was used to select training areas for the maximum likelihood supervised classification process and the another was employed to assess the classification accuracy. According to Congalton and Green (1999), the matrix is the most effective method to evaluate the accuracy. Matrix is the difference between the pixel has been classified and actual pixel matrix error of statistical results. Evaluation results are based on criteria of overall accuracy, producer's and user's accuracy. The values that participated in the accuracy assessment were computed through a method introduced by Congalton and Green (1999). Producer's accuracy is computed by looking at the reference data for a class and determining the percentage of correct prediction for these samples, whereas user's accuracy is computed by looking at the predictions produced for a class and determining the percentage of correct predictions.

2.4 Estimate Forest Volume Using the K-NN Algorithm

The k-nearest neighbours (kNN) algorithm, which is known to be the oldest and simplest approach, is regarded as non-parametric regression. The advantage of this method is due to the fact that no assumptions about the distribution of the variables involved are made (e.g. Efromovich, 1999; Linton & Härdle, 1998). The pixel-wise estimates were derived using the k-nearest neighbours (kNN) method, in which forest parameters (v) are calculated as weighted averages of the k-nearest field plots. The feature space distance (d) between a field plot and a pixel defines how close they are to each other. Feature space distances can be measured by arbitrary metrics. In this study, the Euclidean distance was used in the SPOT 5 spectral space.

For estimation with Euclidean distances, consider the spectral distance $d_{pi,p}$, which is computed in the feature space from the target pixel p (to be classified) to each reference pixel pi for which the ground data is known is as follows:

$$d_{p(pi)} = \left[\sum_{j=1}^{n} \left(x_{p,j} - x_{pi,j} \right)^2 \right]^{\frac{1}{2}} \tag{42.2}$$

where $x_{p,j}$ = digital number for the feature j, n = number of feature in the spectral space.

For each pixel p, take k-nearest field plot pixels (in the feature space) and denote the distances from the pixel p to the nearest field plot pixels by d_{pi}, p,,….,d_{pk},p ($d_{pi,p} \leq \ldots. \leq d_{pk,p}$). The estimate of the variable value for the pixel p is then expressed as a function of the closest units; each such unit value is weighted according to a distance function in a particular feature space. A commonly used function for weighting distances is:

$$W_{(pi)p} = \frac{\frac{1}{d^t_{(p_i)p}}}{\sum_{i=1}^{k} \frac{1}{d^t_{(p_i)p}}} \tag{42.3}$$

where k describes the number of nearest neighbours and t is a distance decomposition factor, typically set to 0, 1, or 2. The sum of weighting $W_{(p_i)p}$ is always equal to 1.

With $t = 2$, the estimate of the variable m for pixel p is then:

$$m_p = \sum_{i=1}^{k} W_{(pi)p} m_{(pi)} \tag{42.4}$$

where $m_{(pi)}$ are the terrestrially recorded values of $i = 1,\ldots k$ pixels, which are located nearest to pixel p in the spectral space. The process is repeated for every pixel and results in intensive computations, depending on the resolution of the sensor and the size of the inventory area (Stümer, 2004).

The *kNN* software developed by Stümer (2004) was used in this study. For this application, two input files are necessary: an 'image file' and a 'field sample file' in ASCII format. The required image data, which are necessary for the *k*NN calculations, are converted from the corrected SPOT 5 bands and NDVI band within masked forest strata into ASCII files. For purpose of comparing between the different estimates, the predictions were run separately for each strum and for the whole forest area. The three input parameters were tested in this study including $t = 2$; and $r = 2$ and k (the number of nearest neighbours) = 5.

Leave-one-out cross-validation (LOOCV) was employed to evaluate the estimate results. This approach leaves one data point out of training data, that is, if there are n data points in the original sample then, n^{-1} samples are used to train the model and one point is used as the validation set. This is repeated for all combinations in which original sample can be separated this way, and then the error is averaged for all trials.

For every trial, accuracy of the predicted volume was evaluated using the root mean square error (RMSE):

$$\text{RMSE} = \sqrt{\frac{\left(\hat{y}_i - y_i\right)^2}{n}} \tag{42.5}$$

where $\widehat{y_i}$ was the estimated parameter on the i*th* observation and y_i was the field-measured parameter, respectively.

To facilitate a comparison with other forest strata, we also used relative RMSE (RMSE, %). The RMSE were calculated using the following:

$$RMSE\% = \frac{RMSE}{a} * 100 \tag{42.6}$$

The kNN was implemented in separate classes, which were obtained from forest stratification based on images classification. At the same time, the estimate was conducted for the whole area without stratification.

3 Results

3.1 Forest Stratification and Accuracy Assessment

The four forest classes were discriminated using MLC method in this study. These classes represented for very heavily degraded forest (Class 1), moderately disturbed forest (Class 2), insignificant disturbance (Class 3), and dense forest (Class 4). Based on field measurement, the forest strata were characterized in Tables 42.1 and the accuracy assessment of classification result was presented in Table 42.2.

The forest strata were distinguished with an accuracy of 85.69% and kappa of 0.79, indicating the substantial agreement between classification result and observations (Landis & Koch, 1977). The confusion matrix in Table 42.2 show most of individual classes had a relatively high accuracy with more than 75% excepting for Class 1 (UA = 68.85%). This indicated there is higher ability of misclassification in

Table 42.1 Confusion matrix of the maximum likelihood classification (for four classes)

	Class 1	Class 2	Class 3	Class 4	Row total	UA (%)
Class 1	42	19	0	0	61	68.85
Class 2	12	138	23	2	175	78.86
Class 3	0	2	67	12	81	82.72
Class 4	0	0	0	172	172	100
Column total	54	159	90	186	Overall accuracy = 85.69% Kappa = 0.79	
PA (%)	77.78	86.79	74.44	92.47		

Table 42.2 Characteristics of stand volume of forest strata

Stand volume (m^3ha^{-1})	Class 1	Class 2	Class 3	Class 4
Mean	91.60	152.66	197.85	286.80
Standard deviation (SD)	22.53	27.71	33.51	56.96
Minimum (min)	45.76	110.63	142.77	212.97
Maximum (max)	135.34	204.76	279.02	412.70
Kurtosis standard	0.517	−0.969	0.847	1.236
Skewness standard	−0.984	−0.087	0.964	−0.398
Number of sample plot	25.00	28.00	39.00	19.00
Confidence level (95.0%)	9.30	10.74	10.86	27.46

the heavily disturbed forest compared to others. This may explain that the forest stand that was heavily impacted, forest structure are destroyed, leading to the high heterogeneity that was found in this stratum. Resulting the low accuracy presented in such stands (Šebeň & Bošeľa, 2010).

Based on field data and result of classification, summary statistics of standing volume for field sample data in the four forest classes was shown in Table 42.3. Skewness and kurtosis should be standardized with a constant, depending on the sample size. The standardized skewness and standardized kurtosis in this case were in the range from −2 to +2. This means the samples collected was able to represent for each stratum.

3.2 *Estimates of Standing Volume for Forest Strata*

The results shown in the Table 42.3 presented the estimate errors of the whole area and each stratum using spectral bands of SPOT 5 and combined SPOT 5 and NDVI data, while Table 42.4 gave those based on NDVI band. The estimate errors indicated the kNN method was quite promising, especially when the forest stands were stratified into the relatively homogeneous classes compared to the estimates

Table 42.3 RMSE (m^3ha^{-1}) and RMSE % for stand volume estimation using spectral SPOT bands and NDVI

Forest stand	SPOT		SPOT + NDVI	
	RMSE (m^3ha^{-1})	RMSE %	RMSE (m^3ha^{-1})	RMSE %
Estimate without stratification	47.06	26.73	46.81	26.10
Class1	32.72	37.27	25.83	26.82
Class2	18.09	11.52	20.84	13.67
Class3	26.87	13.35	27.55	14.54
Class4	30.87	10.68	28.66	11.03
General calculation of the four classes	27.70	18.64	26.70	16.71

Table 42.4 RMSE (m^3ha^{-1}) and RMSE % for stand volume estimation using NDVI

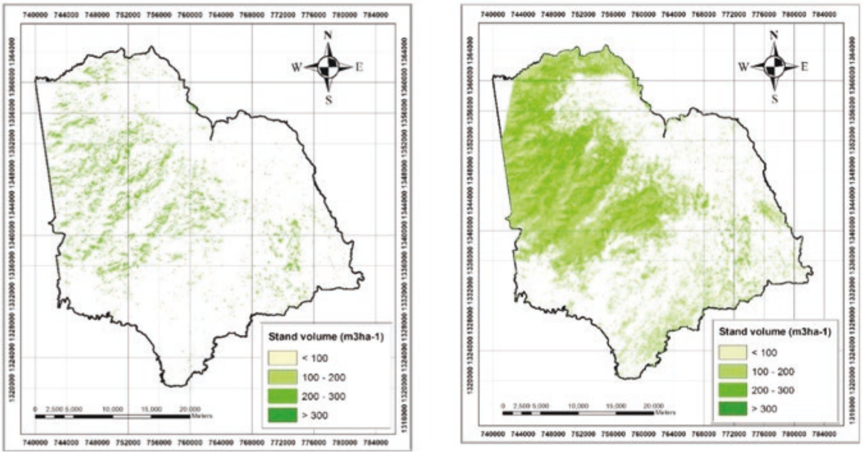
	RMSE (m^3)	RMSE %
Estimate without stratification	53.30	28.57
Class1	24.05	28.10
Class2	21.05	14.06
Class3	35.10	17.22
Class4	64.24	20.99
General calculation of the four classes	37.72	20.95

performed for the whole area without consideration on state of disturbed levels. This presented in both data set of SPOT and NDVI.

Among strata, the lowest accuracy of the estimation was found by Class1 in both SPOT and NDVI image. This suggests that the predictions from forest well managed were more accurate than the heavily degraded forest. There also was a small difference of RMSEs among the remaining classes. In almost all cases, the estimations performed using the SPOT or the SPOT + NDVI gave lower errors than the NDVI except for Class1. This may be the fact the forest stand that was strongly impacted the vegetation index variety becomes more optimal than using the SPOT image. The result also indicated that though the combination SPOT and NDVI improved the estimate results, the difference was not insignificant.

The difference of stand volume estimated and field volume ranged from 18.0 m^3ha^{-1} (estimated from SPOT) to 64.0 m^3ha^{-1} (estimated from NDVI); 12% and 21% of the mean measured value, respectively. The lowest error of 18.0 m^3ha^{-1} was given by Class2 which was classified as moderately disturbed forest and the highest was from Class4 which was discriminated as the dense forest. However the higher RMSE% was found in the estimate from Class2 with 11.52% comparing those of 10.68% in Class4. This was due to the mean stand volume of Class4 was of 286.8 m^3ha^{-1} while those of Class2 was of 152.66 m^3ha^{-1} (Table 42.2). Therefore, the comparisons should be considered among values of relative RMSE (%).

The worst predictions were found in all cases of estimate for the whole area without stratification with RSME of 47.06 m^3ha^{-1}, 46.81 m^3ha^{-1} and 53.30 m^3ha^{-1} corresponding to RMSE% of 26.72%, 26.10% and 28.57% for SPOT, SPOT+NDVI and NDVI, respectively. However, the results were significantly improved when the estimates were performed for each stratum. Among the strata, the lowest estimate was given by Class1 corresponding to heavily disturbed forest with RMSE of 32.72 m^3ha^{-1} (SPOT 5) and RMSE% of 37.27%. The difference between actual and estimated volume in other classes was impressively low with RMSE% <20%. Although the lowest value of RMSE% was obtained in Class4 both SPOT and SPOT+NDVI, the higher result was observed by NDVI. It may be the NDVI was saturated in the stable forest stands, for example, Class4. Conversely, the lower error was gained from Class1 using the NDVI compared to other (SPOT and SPOT+NDVI). In the forest stand which was heavily disturbed, NDVI data became a better choice in estimating the stand volume. In generally, the multi-spectral bands (e.g. SPOT or SPOT + NDVI) gave the better predictions compared to NDVI in this case. RMSE% of 18% and 16.71% were gained for the whole strata compared to the prediction of volume based only on NDVI with RMSE of 37.72 m^3ha^{-1} and RMSE% of 20.95%. Some authors compared the estimate errors of stand volume among sizes of area (e.g. Fazakas, Nilsson, & Olsson, 1999; Reese, Nilsson, Olsson, & Sandström, 2002). Reese et al. (2002) reported that when the accuracy of the estimates is assessed over larger areas, the errors are lower. The RMSE reduced to 10% RMSE over a 100 ha aggregation compared to 17% RMSE over an area of 19 ha aggregation. Meanwhile, Gu et al. (2006) showed the errors in the volume estimates by tree species were clearly higher than those of the total volume estimates. Specifically, the volume of Larix forest was estimated with a relative error of 51.7%,



Stand volume map prediected from stratum of Class4 (insignificant disturbance)

Map of stand volume predicted from SPOT 5

Fig. 42.1 Forest stand volume estimated using SPOT 5

while the estimation errors for the Korean pine and broad-leaved tree species were over 71.7% and 88.19%, respectively. Franco-Lopeza, Ekb, and Bauerb (2001) reported RMSE forest volume was 48.68, 54.58 m^{3}ha^{-1} for coniferous forests, which are relatively few species. Reese et al. (2004) showed 33% RMSE (85 m^{3}ha^{-1}) for the estimates of total wood volume in the highly managed coniferous forest in Norway. In the current study, the output result provided another example of assessing the effect of volume estimate based on the homogenous forest stands rather than estimate for the whole forest area without stratification. Moreover, this result indicated that although the non-parametric method kNN is simple, the application presented as the promising method in estimating stand forest volume (Fig. 42.1).

4 Conclusions

Although there have been some studies on applying remote sensing data to the management of forest resources in Vietnam, most studies have focused on discrete variables such as the development of current status maps and land cover rather than estimating forest attributes, for example, producing forest volume map. Therefore, finding suitable solutions with updated information and low cost to quantify forest resources is essential especially in forest management. The non-parametric method applied in this study shows its potential in estimating forest continuous variables, for example, stand volume. The estimate was highly accurate, with an overall accuracy of around 80%. The better accuracy was found when the estimates were applied for separable stratum; the results showed a significant improvement compared to the estimate for the whole area. The overall errors for the whole area was around 25%, 26% and 28% for SPOT image, combined SPOT and NDVI image, and NDVI, respectively; while these ranged 16–20% for SPOT 5, SPOT + NDVI, and NDVI, respectively. Considering among forest stratum, except for the heavily impacted forest stand, the estimation errors were 37% (SPOT), 26% (SPOT+NDVI) and 28% (NDVI), the remaining classes (2,3,4) were predicted with quite high accuracies. The study provided an example to quantify forest resource using approach of forest strata. The use of non-parameter regression kNN to estimate the stand volume for strata forest in this study may be applicable potentially in complex structures of degraded forests in different levels such as Vietnamese natural forest stands.

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