RESEARCH ARTICLE

Assessment of different remote sensing data for forest structural attributes estimation in the Hyrcanian forests

Nooreddin Noorian, Shaban Shataee-Jouibary* and Jahangir Mohammadi

Forestry Department, Gorgan University of Agricultural Sciences, and Natural Resources, 386, Gorgan, Iran

Abstract

Aim of the study: The objective of the study was the comparative assessment of various spatial resolutions of optical satellite imagery including Landsat-TM, ASTER, and Quickbird data to estimate the forest structure attributes of Hyrcanian forests, Golestan province, northern Iran.

Material and methods: The 112 square plots with area of 0.09 ha were measured using a random cluster sampling method and then stand volume, basal area, and tree stem density were computed using measured data. After geometric and atmospheric corrections of images, the spectral attributes from original and different synthetic bands were extracted for modelling. The statistical modelling was performed using CART algorithm. Performance assessment of models was examined using the unused validation plots by RMSE and bias measures.

Main Results: The results showed that model of Quickbird data for stand volume, basal area, and tree stem density had a better performance compared to ASTER and TM data. However, estimations by ASTER and TM imagery had slightly similar results for all three parameters.

Research highlights: This study exposed that the high-resolution satellite data are more useful for forest structure attributes estimation in the Hyrcanian broadleaves forests compared with medium resolution images without consideration of images costs. However, regarding to be free of the most medium resolution data such as ASTER and TM, ETM+ or OLI images, these data can be used with slightly similar results.

Keywords: Forest structure attributes; quickbird; ASTER; TM; CART algorithm; Hyrcanian forests.

Introduction

The forest has a significant role in human life. It not only has to provide goods for consumption but it also has an ecological, environmental, and aesthetic role in human life. Forest structural attributes such as volume, basal area, and number of trees per unit area are important data needed for effective forest management (Gebreslasie *et al.*, 2010). Hyrcanian forests comprise a diverse vegetation cover in the north of Iran and are increasingly fragmented, degraded and converted to other forms of land use (Mohammadi *et al.*, 2010). The forest's structural attributes are traditionally gathered by ground-based field measurements using hand-held equipment. These measurements are generally expen-

sive, time-consuming and labour intensive, as well as difficult to perform, especially in mountainous and dense forests (Mohammadi *et al.*, 2011). Satellite remote sensing is an alternative source and new tool for forest management and surveying, particularly in large areas. Rapid improvements in remote sensing technology have led to various types of sensors, such as multispectral, hyper spectral, ultraviolet, thermal sensors, light detection and ranging (Lidar), radio detection and ranging (radar), and other sensors. Each type of sensor has been designed for specialized purposes, tasks and different applications (Kalbi, 2011). These new potential sources have been shown to be appropriate tools to assess and monitor forest attributes with reasonable accuracy levels (Hyyppa *et al.*, 2000). Satellite sensor

data have recently been used in a multisource forest inventory for estimating forest characteristics due to their advantages including large geographic coverage and large spectral range (Tuominen & Haakana, 2005). In the past two decades, many researchers (see table 1) have focused on the extraction and retrieving of forest stand parameters such as stand volume, basal area, DBH, and tree stem density using medium-to-high resolution optical sensor data.

This research has used different remote sensing sources from aerial photos to satellite based images, with various spatial, radiometric, or spectral resolutions. In some occasions, the results of previous studies were not satisfactory for managers according to forest condition such as forest composition, forest structure, and topography complexity. The comparative studies for investigation into the capability of various image sources based on spatial or spectral characteristics can help to choose suitable images for the extraction of the desired information. Few research studies have compared the effect of different spatial resolutions from different image sources including very high-spatial resolution (airborne- or space-borne systems) to medium spatial resolution imagery in a same forest. For instance, Hyyppa et al., (2000) used various image sources, such as aerial photographs, SPOT Pan, SPOT XS, and Landsat-TM, and compared the accuracy of retrieving the following forest stand variables: stem volume, mean tree height and basal area. They found that using high-resolution image types had better estimates compared to medium resolution images (i.e., SE% of 46, 50, 56 in stem volume and 38, 42, 47 for basal area estimation, respectively for aerial photos, SPOT-XS and Landsat-TM).

It has been confirmed that using high-spatial resolution imagery may lead to estimates of high-precision results, especially for the extraction of forest attributes, due to its ability for finer detection and recognition of spectral reflections of the canopy crown and lower mixed pixels. However, medium spatial resolution imagery has been the most popularly used data in stand and plot level estimations. Comparative studies in mixed and multi-layered forests such as Hyrcanian forests could be useful to determine suitable image sources to extract forest structure attributes.

In recent years, non-parametric algorithms such as decision tree-based algorithms (Breiman et al., 1984) and their variants like CART (classification and regression tree) have been widely used in different studies due to their simple interpretation, high precision, and ability to characterize complex interactions among variables (Cutler et al., 2007). Non-parametric algorithms have obvious advantages over parametric-based algorithms for multisource predictive forest mapping. One major drawback of parametric-based algorithms is that they assume a particular statistical distribution in the dataset, which is usually not compatible with multisource data. Nevertheless, non-parametric-based

Table 1. The previous studies performed by different sources and algorithms

Study	Variables	Data sources	Algorithm	RMSE (%)	R^2
Trotter et al., (1997)	Stand volume	TM	Linear Knn	-	0.3
Kilpelainen and Tokola (1999)	Stand volume	TM	RSP	-	0.60
Muukkonen and Heiskanen (2005)	Stand volume	ASTER	Nonlinear ANN	44.7 41	
Hall et al., (2006)	Stand volume	ETM+	Linear	-	0.3
Sivanpillai et al., (2006)	Tree density	ETM+	linear	-	0.60
Huiyan et al., (2006)	Stand volume	TM	Knn	44.2	-
Wolter et al., (2009)	Stand volume, Basal area	SPOT-HRG	OLS	-	0.53, 0.74
Mohammadi et al., (2010)	Stand volume, Tree density	ETM+	CART Linear	43, 73 67, 80	0.43, 0.73
Gebreslasie et al., (2010)	Stand volume, Basal area, Tree density	ASTER	Linear	-	0.51, 0.67, 0.65
Kalbi et al., (2014)	Stand volume, basal area	ASTER, SPOT-HRG	CART	18.2, 15.8	0.59
Shataee et al., (2012)	Stand volume, Basal area, Tree density	ASTER	Knn SVM, RF	26.86,20.20, 21.53 28.54, 19.35, 22.09 25.86, 18.39, 20.64	- - -

Abbreviations: RMSE, Root mean square error; Knn, K nearest neighbor; RSP, Reference sample plot; ANN, Artificial neural network; OLS, Ordinary least squares; CART, Classification and regression tree; SVM, Support vector machine; RF, Random forest.

algorithms make no assumption on data distribution, and therefore avoid the significant error source. This means that they are free from assumptions of any given probability distribution, and observations are assumed independent of each other (Sironen *et al.,* 2010). Many studies have shown that non-parametric methods provide better estimation results. In some studies, such as Sarunas (1997), it has been demonstrated that even with small training samples, non-parametric estimation algorithms provide better results than parametric ones. Among non-parametric algorithms, tree based algorithms are more famous and more commonly used for both forest attribute estimation and classification. In this paper, the capability of Quickbird, ASTER, and TM data were compared to estimate forest structural attributes using classification and regression trees algorithm (CART) as one of the non-parametric algorithms.

In the past several years, classification and regression tree-based analyses have been implemented in several software programs, and used in many remote-sensing applications (Huang & Jensen, 1997; Lawrence & Wright, 2001; Cooke & Jacobs, 2005). The use of non-parametric methods for land cover classification has increased in the past decade. Aertsen *et al.,* (2010) investigated the performance of non-parametric techniques such as CART compared to parametric techniques for the prediction of site index in Mediterranean mountainous forests. Moisen & Frescino (2002) and Wang *et al.,* (2005) evaluated these techniques for the prediction of several species-independent forest characteristics in the interior western United States and for the spatial prediction of site index of Lodge pole pines in Canada. These studies concluded that non-parametric approaches were more effective compared to parametric ones.

The objective of research was comparison of various medium (TM and ASTER) and high (Quickbird) spatial resolution satellite images by CART algorithm for estimation the quantitative forest attributes of the Shastkalateh's forest as a part of the Hyrcanian forests with mixed and multi-layered hardwood stands, in the Golestan province, north of Iran.

Materials

Study area

The Hyrcanian vegetation zone is a green belt stretching over the northern slopes of Alborz Mountain and covers the southern coasts of the Caspian Sea. This zone is rich in point of species diversity and includes 80 woody species (trees and shrubs) dominated with hardwoods. The Iranian Hyrcanian forests extend into the three provinces of Gilan, Mazandaran, and Golestan. This research was performed in the Shastkalateh forest as a small part of the eastern Hyrcanian forest located in the Golestan province with a 1,714 hectares area. The study area is positioned between 36° 43′ to 36°45′N latitudes and 54°21′ to 54°24′E longitudes (Fig. 1) and elevations range from 210 to 1010 m above mean sea level, with slopes of 5% to 45%. The main slope aspects of the site are west and southwest aspects. The main and dominant tree species are beech (*Fagus orientalis*), hornbeam (*Carpinus betulus*), Persian parotia (*Parrotia persica*), chestnut-leaved oak (*Quercus castaneafolia*), coliseum maple (*Acer cappadocicum*), velvet maple (*Acer velutinum*), Caucasian alder (*Alnus subcordata*) and date palm (*Diospyros lotus*). The Shastkalateh's forest is under a forestry management plan with a selective cutting treatment method.

Data

Field data

The in-situ data were gathered in the summer of 2010 (in line with season of images) and on 23 clusters with 5 plots and 112 plots in the natural stands (95 plots) and planted stands (17 plots) with homogenous unities in terms of slopes, aspects, and forest types. The distance between plots in each cluster was 75 m and the plots were square with an area of 30×30 (0.09 ha) m (Fig. 1). The coordinates of the centre of each plot were accurately registered using a DGPS device in a post-processing kinematics (PPK) method. In each plot, the species name, stand height (measured to the nearest tree) and diameter at breast height (DBH) of trees with a diameter greater than 7.5 cm at breast height were taken. Singletree volume in plots was calculated using a local volume table, containing diameter at breast height ($d_{1.3}$) and height, to estimate the volume of different species in the plots. Plot level volume was computed throughout, adding total singletree volumes. Finally, the volume per hectare (m³/ha) was estimated using the total volume of all trees in each plot. The measured DBH of trees was used to determine basal area. In addition, the tree density was computed through counting of measured trees in each plot.

Remote sensing data

Data used for this study included Quickbird images from 7 October 2007, ASTER images from 3 July 2006,
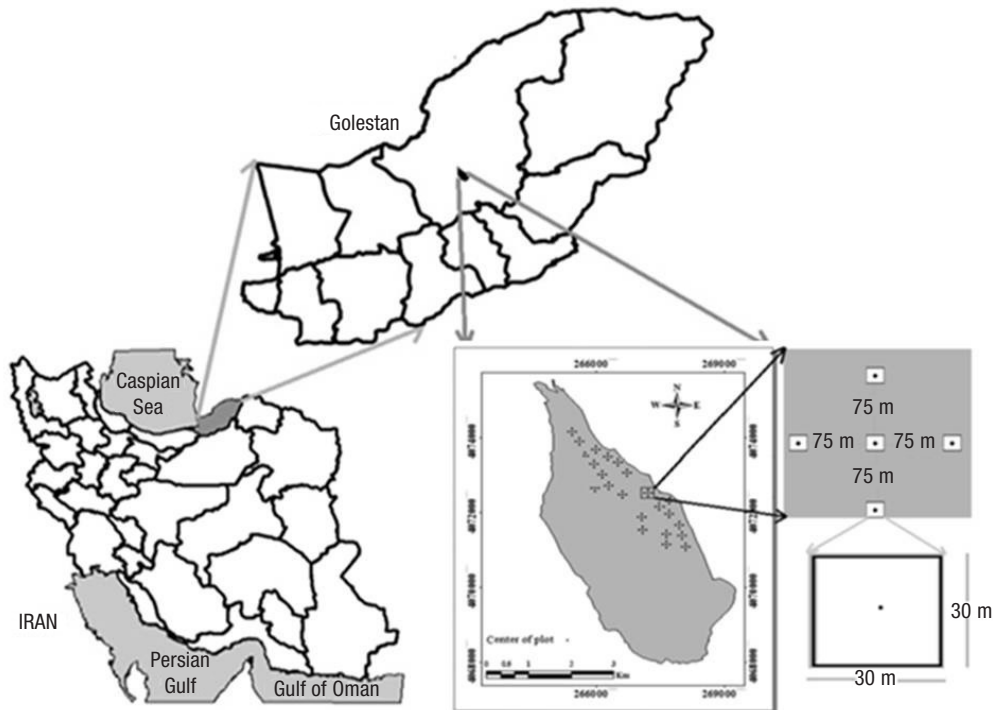
Figure 1. Location of study area in the Golestan province, northern Iran, and spatial distribution of field plots.

and Landsat-5 TM images from 17 September 2010. The dates of images are ranging during summer season so that trees do not have phenology differences due to completing leaf growing and there were not considerable cover changes in the period of five years. The projection system was UTM zone 40N, Datum WGS 1984. Table 2 summarizes the acquisition of the data in detail.

Methods

Pre-processing of satellite data

In this study, the image datasets were georeferenced to the UTM coordinate system using ground control points (GCPs) and second-order polynomial equations. The Quickbird images were georeferenced and ortho-rectified using 24 GCPs collected from DGPS and a digital elevation model (DEM) derived from a 1:25,000 topography map (Yazdani, 2011). The ASTER and TM images were rectified with Quickbird images using 25 and 30 GCPs, respectively. The total root mean square errors (RMSE) of images were obtained approximately of 0.36 and 0.25 for ASTER and TM images, respectively. The geometric precision of images was also verified using road and river vectors.

In this study, due to a lack of some information required for accurate atmospheric models, the cosine

estimation of atmospheric transmittance (COST) absolute radiometric correction model (Chavez & Pat, 1996) was applied on each image. This model consists of a modification of the dark-object subtraction (DOS) method by including a simple multiplicative correction for the effect of atmospheric transmittance.

Image processing

After geometric rectification and atmospheric corrections, some suitable processing analyses including tasselled cap transformation (greenness, brightness, and wetness components), standardized principal components (PCA), Pansharpning (for Quickbird images), vegetation indices (Table 3) and texture analyses were performed to produce useful and correlated artificial for quantifying and enhancing biophysical characteristics. The texture analysis is done on VNIR band of ASTER and Quickbird images with grey level co-occurrence matrix (GLCM) indices (Mean, Variance, Homogeneity, Contrast, Dissimilarity, Entropy, Angular second moment, Correlation, GLDV angular second moment, GLDV entropy, GLDV mean, GLDV contrast, Inverse difference). These were included in the statistical analysis via main bands for prediction of forest structural attributes in the regression modelling.

Table 2. Information of satellite imagery used in this study

Source	Day and month	Year	Bands	Number of bands	Pixel size (m)	Quantization level
Quickbird	October 7	2007	Multispectral	4	2.5	11-bit
			Panchromatic	1	0.68	
ASTER	July 3	2006	VNIR	3	15	8-bit
			SWIR	6	30	
Landsat5-TM	September 17	2010	Multispectral	6	30	8-bit

Table 3. Most popular used spectral vegetation indices related to forest structure attributes

Index	Equation	References
Normalized difference vegetation index (NDVI)	$(NIR - RED)/(NIR + RED)$	37
Green Normalized Difference Vegetation Index (GNDVI)	$(NIR - G)/(NIR + G)$	37
Normalized ratio (NR)	$RED - NIR$	38
Simple ratio (SR)	NIR/RED	38
Near Infrared Ratio (NIR)	$TM4/TM3$	39
Difference vegetation index (DVI)	$NIR - RED$	40
Modified soil adjusted vegetation index (MSAVI2)	$(0.5) * \{2 * (NIR + 1) - Sqrt[(2 * NIR + 1)^2 - 8 * (NIR - R)]\}$	41
Ratio Vegetation Index (RVI)	$NIR/(RED + GREEN)$	40
Transformed Vegetation Index (TVI)	$(TM5 - TM3)/(TM5 + TM3)$	39
Contrast Reflectance in Visible and Near Infrared (VNIR1)	$(TM4 - TM1)/(TM4 + TM1)$	39
Middle Infrared Vegetation Index (MIRV2)	$(MIR - RED)/(MIR + RED)$	42

NIR, Near infra red; G, Green; MIR, Middle infra red.

Statistical analyses

In this study, statistical analyses were performed by R-2.14.2 (2011-12-22) software (R core Team, 2012). The spectral values of the main and artificial images of the three sensors were extracted by the Zonal statistics function in ArcGIS software corresponding to ground plots. Using 85% of plots (95 plots), the CART algorithm was conducted to evaluate relationships between forest structural attributes of volume, basal area, and number of stem trees per hectare as dependent and spectral data extracted from main and artificial images as independent variables. The CART algorithm is a nonparametric modelling approach that can explain responses of a dependent from a set of independent continuous or categorical variables. The CART models recursively partitioned the data to find increasingly homogeneous subsets based on independent variable splitting criteria using variance-minimizing algorithms. This model produces outcomes that are unaffected by monotone transformations and differing scales of measurement among predictors. Regression trees are insensitive to outliers and can accommodate missing data in predictor variables using surrogates. The dependent data are partitioned into a series of descending left and right child nodes derived from parent nodes. Once the partitioning has ceased, the child nodes are des-ignated as terminal nodes. Pruning of trees is often necessary to avoid over-fitting of data, often accomplished by setting aside a portion of the training data for pruning. A cross validation methodology is applied for pruning to outcome prediction. Regression trees are insensitive to outliers, and can accommodate missing data in predictor variables using surrogates. For more details on the CART model, refer to Breiman *et al.,* (1984).

Model evaluation

Of the plots used, 85% (95 plots) were used for modelling and the remaining 15% (17 plots) were used to evaluate the model outputs. The reliability of estimates was measured by adjusted coefficient of determination (R^2adj), root mean square error (RMSE) [1], percentage RMSE [2], Bias [3], and percentage bias [4] (Makela & Pekkarinen, 2004).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad \text{[Eqs. 1]}$$

$$RMSE\% = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}{\hat{y}} \times 100 \qquad \text{[Eqs. 2]}$$

$$\text{Bias} = \frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i \right) \qquad \text{[Eqs. 3]}$$

$$\text{Bias \%} = \frac{\frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)}{\hat{y}} * 100 \qquad \text{[Eqs. 4]}$$

Where, $\hat{y}_i$ is predicted value, y_i is the observed value, $\bar{y}$ is the mean of the observed values, and n is the number of observations in the test dataset.

Results and Discussion

Descriptive statistics of field data

The preliminary descriptive statistics results showed that stand volume, basal area and tree density ranged from 22.84 to 647.82 m³/ha, 3.29 to 52.57 (m²/ha) and 111.10 to 966.57 (n/ha), respectively. The mean stand volume was 294.64 m³/ha with standard deviation of 141.21 m³/ha, the mean basal area was 25.40 m²/ha with standard deviation of 10.09 m²/ha and the mean tree density was 366.98 n/ha with a standard deviation of 194.55. Table 4 represents a full range of stand structure attributes in the study area.

Estimating forest characteristics

Estimating stand volume

The results of CART model implementation to create the relationship between spectral values of used images and stand volume are shown in the table 5 as the best predictors of stand volume, with the adjusted R² of 0.61, 0.76 and 0.71 and RMSE of 50.96, 120.92, 102.39 m³/ha, for Quickbird, ASTER and TM images, respectively (Table 6).

The obtained R² values of this study were higher than obtained by others (Trotter *et al.*, 1997; Hall *et*

al., 2006; Mohammadi *et al.*, 2010; Gebreslasie *et al.*, 2010; Wolter *et al.*, 2009; Kalbi *et al.*, 2014). In contrast, the obtained RMSE values were lower than RMSE of different studies (Tokola & Heikkila, 1997; Fazakas *et al.*, 1999; Hyyppa *et al.*, 2000, Hyvonen, 2002; Makela & Pekkarine, 2004; Huiyan *et al.*, 2006; Muukkonen & Heiskanen, 2005).

The regression tree model for stand volume estimation using Quickbird images as the best image, which could produce better estimations, is shown in fig. 2 (for ASTER and TM images please see Figures S1 and S2 [supplementary]). The models indicate that blue, mean (VNIR1) and mean of blue bands were the most important variables to model the stand volume, and could be explained by three image dates (Table 5). The performance results of using different data sources by CART for stand volume estimation showed that Quickbird images could produce estimations with lower absolute and percentage RMSE and bias compared to using ASTER and TM data. However, estimations produced using ASTER and TM data were almost similar and had very slight differences. For volume estimation, the results obtained from TM data were better than those obtained from the ASTER data were. Comparative results of implementations are given in Table 6.

Estimating basal area

The results of CART model implementation to create the relationship between spectral values of used images and basal area are shown in the table 5 as the best predictors of basal area with the adjusted R² of 0.50, 0.73, and 0.70 and RMSE of 2.44, 10.03, and 9.08 m² ha⁻¹, for Quick bird, ASTER and TM images, respectively (Table 6).

The R² values obtained in this study to predict basal area using Quickbird image were lower than ones were obtained by other researches (Gebreslasie *et al.*, 2010; Wolter *et al.*, 2009; Kalbi *et al.*, 2014). In addition, the RMSE values were lower than those values obtained

Table 4. Descriptive statistics of the field inventory data

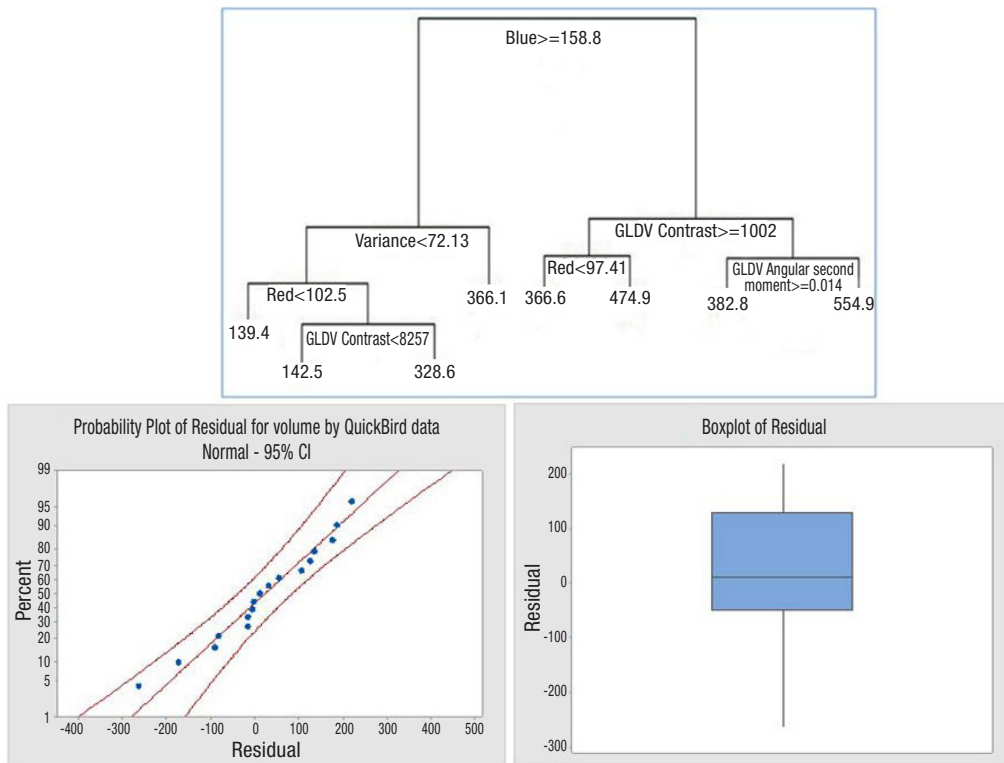|	Stand volume (m³ ha⁻¹)		Basal area (m²/ha)		Tree density (n/ha)	
	Model	**Validation**	**Model**	**Validation**	**Model**	**Validation**
Number	95	17	95	17	95	17
Mean	294.64	300.61	25.40	25.96	366.98	373.81
Standard Deviation	141.21	119.62	10.09	9.49	194.55	208.66
Range	624.98	467.93	49.28	34.46	855.47	644.38
Minimum	22.84	65.93	3.29	8.03	111.10	177.76
Maximum	647.82	533.81	52.57	42.49	966.57	822.14

Figure 2. Binary regression tree (top) and probability (left), and box plot (right) of residual CART model for stand volume using Quickbird data.

Table 5. The variables selected by the best models developed for each of three image sources

Attribute	Source	Selected variables by model
Stand volume	Quickbird	band1, band 3, Variance, GLDV Contras and GLDV Angular second moment
	ASTER	Mean (VNIR1), PCA2, Homogeneity (VNIR1), Contrast (VNIR2) and Correlation (VNIR3)
	TM	band 1, band 4 (NIR), greenness, and GNDVI, Ratio and NR
Basal area	Quickbird	GLDV Entropy, Band1, ARVI index, Brightness and GLDV Contrast
	ASTER	PCA1, PCA2, Mean (VNIR1), Variance (VNIR1), Homogeneity (VNIR3) and Correlation (VNIR3)
	TM	Greenness, band1, PCA3, GNDVI, Ratio and ARVI
Tree density	Quickbird	Entropy, Variance, Mean and GLDV Contrast,
	ASTER	greenness, brightness, Msavi2, GLDV Angular second, Dissimilarity and Homogeneity
	TM	PCA3, band1, band2, band3 and Msavi2

by direct estimation to predict basal area (Gebreslasie *et al.,* 2010; Kalbi *et al.,* 2014).

The R[2] values obtained in this study using ASTER images were higher than those that obtained through direct estimation to predict basal area (Gebreslasie *et al.,* 2010; Wolter *et al.,* 2009; Kalbi *et al.,* 2014).

The R[2] values obtained in this study using TM images were higher than those that obtained through direct estimation to predict basal area (Hyyppa *et al.,* 2000; Gebreslasie *et al.,* 2010). In addition, the obtained RMSE values were higher than those obtained by direct estimation and used to predict basal area (Gebreslasie *et al.*, 2010; Wolter *et al.*, 2009; Kalbi *et al.,* 2014).

The results of regression tree model for basal area estimation using Quickbird images as the best image, which could produce better estimations, is shown in Fig. 3 (for ASTER and TM images please see Figures S3 and S4 [supplementary]). The results indicated that GLDV entropy, PCA1, and greenness were the most important variable determining basal area, could be explained by three image dates above, respectively (Table 5). The results of using different data sources in CART performances for estimate basal area/ha showed that Quickbird images could produce estimations with lower absolute and percentage RMSE and bias compared to using ASTER and TM data. However, estimation using ASTER and TM data produced slightly

Table 6. Results of the best CART models performance to estimate the variables using data sources

| Attribute	Source	Validation metrics				
		Adjusted R^2	RMSE (m³ ha⁻¹)	RMSE (%)	Bias (m³ ha⁻¹)	Bias (%)
Stand volume (m³ ha⁻¹)	Quickbird	0.61	50.98	20.35	3.71	1.48
	ASTER	0.76	120.92	40.22	52.71	17.5
	TM	0.71	102.39	34.06	0.57	0.19
Basal area (m² ha⁻¹)	Quickbird	0.50	2.44	12.10	0.71	3.52
	ASTER	0.73	10.03	38.67	2.08	8
	TM	0.70	9.08	35	1.47	5.68
Tree density/ha (nha⁻¹)	Quickbird	0.59	125	30.36	2.98	0.71
	ASTER	0.80	219.4	58.68	10.18	2.72
	TM	0.67	210.64	56.34	9.71	2.62
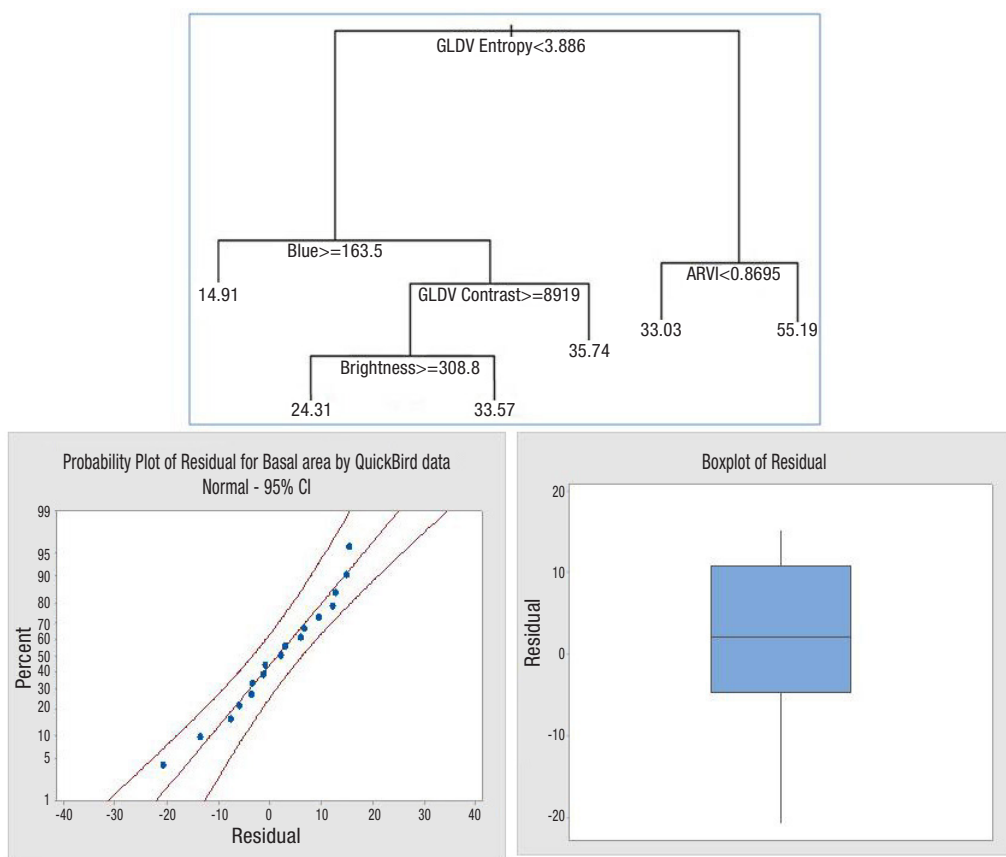
Figure 3. Binary regression tree (top) and probability (left), and box plot (right) of residual CART model for basal area/ha using Quickbird data.

similar results. Comparative results of implementations are given in Table 6.

Estimating tree density/ha

The results of CART model implementation to create the relationship between spectral values of used images and basal area are shown in the table 5 as the best predictors of basal area with the adjusted R^2 of 0.59, 0.80 and 0.67; and RMSE of 125, 219.4 and 210.64 n/ha for Quick bird, ASTER and TM images, respectively (Table 6). The obtained R^2 values using Quickbird were lower than ones that obtained through direct estimation to predict tree density by Sivanpillai *et al.,* (2006), Gebreslasie *et al.,* (2010), Mohammadi *et al.,* (2010) and Kalbi *et al.,* (2014). In addition, RMSE values obtained in this study were lower than values obtained when direct estimation was used to predict tree density by Sivanpillai *et al.,* (2006).
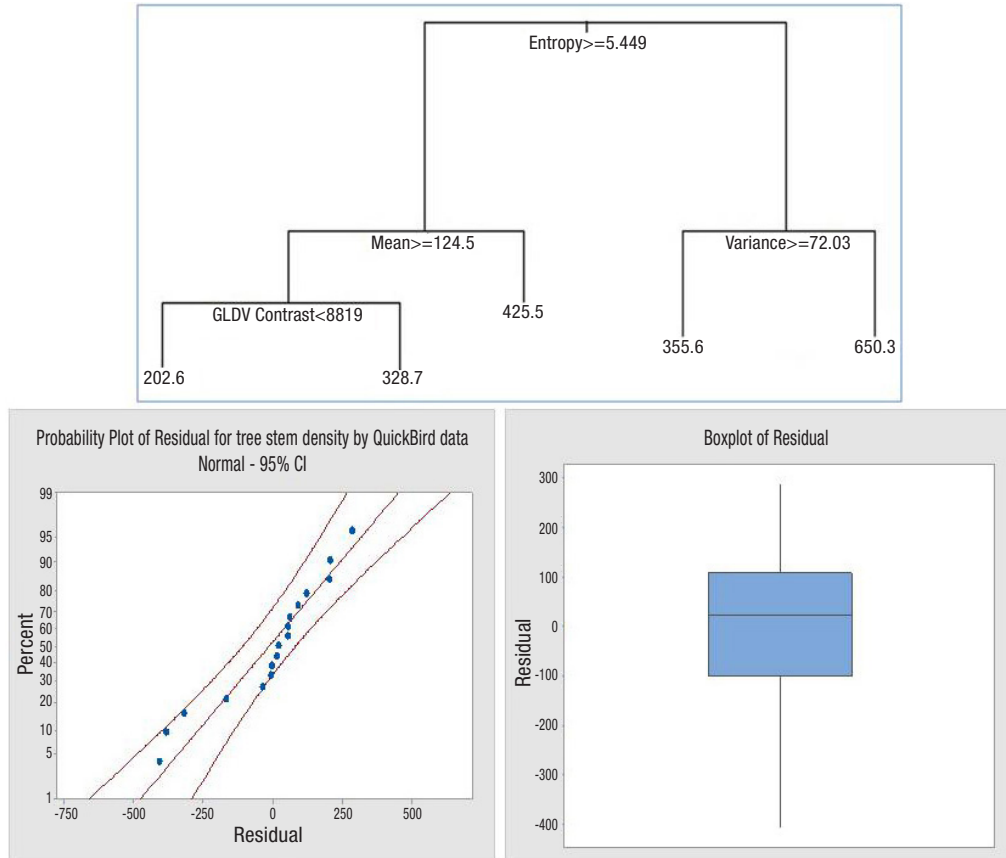
Figure 4. Binary regression tree (top) and probability (left), and box plot (right) of residual CART model for tree density/ha using Quickbird data.

The R^2 values obtained in this study using ASTER images were higher than obtained through direct estimation to predict tree density by Sivanpillai *et al.,* (2006) and Gebreslasie *et al.,* (2010). In addition, the RMSE values obtained in this study were higher than results obtained the studies that were used direct estimation to predict stand volume (Kalbi *et al.,* 2014 and Shataee *et al.,* 2012). The RMSE and R^2 values of tree density values were favourably compared to those obtained by Sivanpillai *et al.,* (2006); Gebreslasie *et al.,* (2010); and Freitas *et al.,* (2005).

The regression tree model for tree density estimation using Quickbird images as the best image, which could produce better estimations, is shown in Fig. 4 (for ASTER and TM images please see Figures S5 and S6 [supplementary]). The results indicated that entropy, greenness, and PCA3 were the most important variables in determining tree density/ha, which could be explained by the three-mentioned images, respectively (Table 5). The results of CART performances by different data sources to estimate tree density showed that Quickbird images could produce estimations with lower absolute and relative RMSE and bias compared to ASTER and TM data. However, estimations of both data were slight-

ly similar (Table 6). Fig. 5 show maps of estimates by CART algorithm using Quickbird data in the study area.

Conclusions

The relationships between reflectance data recorded by the spectral data and forest structural attributes were analysed through the CART algorithm in this study.

Performance assessment of models was examined using RMSE and bias on the unused plots. The results showed that Quickbird satellite data for each three attributes (stand volume, basal area, and tree stem density) have better results than ASTER and TM satellites. However, estimations of ASTER and TM images showed slightly similar results. It seems that the results obtained from TM data were better than results obtained from ASTER data. This priority could be due to using texture analysis on the ASTER image, and retrieval quantities variables using texture analysis ASTER image cannot be very precise.

Although results of this study are valuable and important for extracting and retrieving forest quantity information, and it could provide valuable information
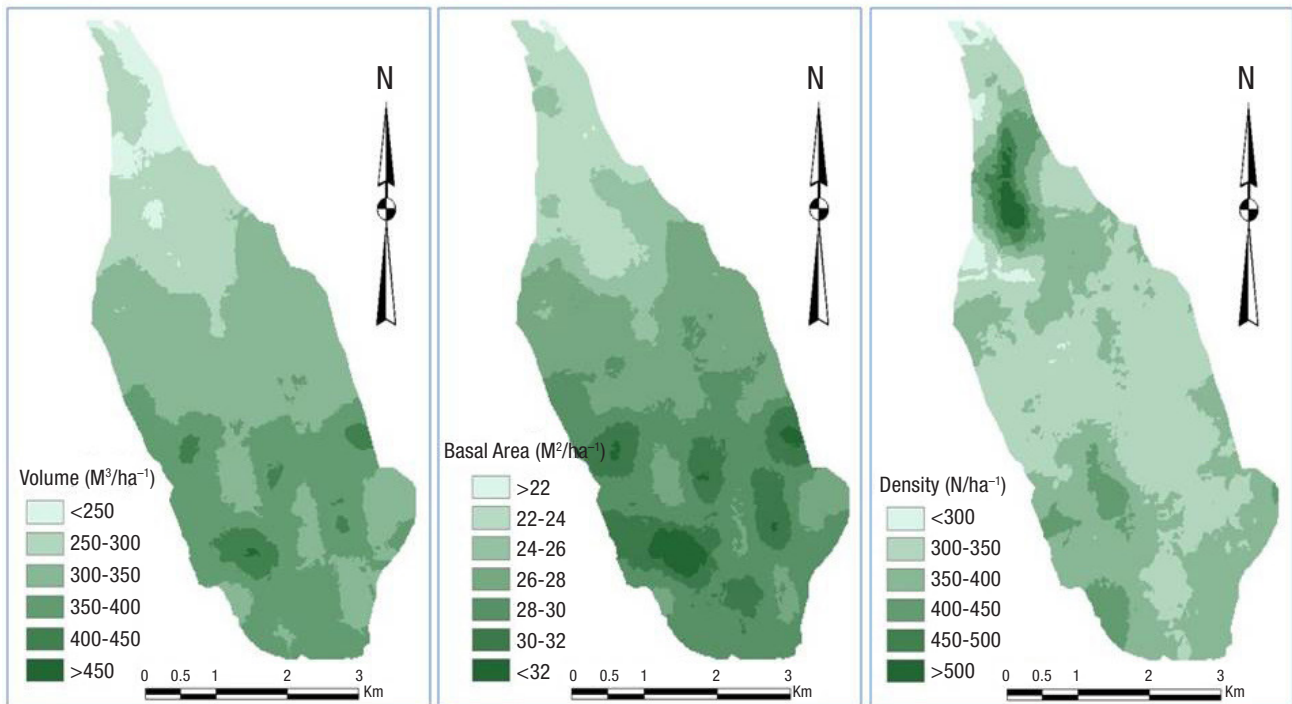
Figure 5. The maps of variables estimated by CART algorithm using Quickbird data.

about changes in stand structure and help forest re-source managers to devise suitable management plans. However, the outcomes of this study should be again tested in similar forests elsewhere and/or be adopted in other types of forests, which have same composition and structure. We suggest that the procedure adopted in this study is tested in other areas while investigating the effects of other satellite data.

The results of modelling showed that in spite of priority of Quickbird data compared to ASTER and TM data to estimate the forest attributes, none of these estimation is not enough for accurate variable mapping for executive planning. The causes of do not be ade-quate the estimations refer to some things. First, these images are coming from optical remote sensing sourc-es, which are producing the 2D information from re-flections of canopy surfaces; however, for estimation of stand volume using the 3D information such as using Lidar data could be improve the estimations. Second, complexity of forest stands in points of multi-layers and species composition can be effect on the inaccurate estimations. Using of combination the optical with Lidar data can be useful for improving the estimations.

In conclusion, the results of this study demonstrated that the reflectance values recorded by satellite data are related to spatial resolution. Updating information periodically through satellite remote sensing technol-ogy could provide valuable information about changes in stand structure and help forest resource managers to devise suitable management plans.

References

Aertsen W, Kint V, Orshoven JV, Ozakan KA, Wuysa B, 2010. Comparison and ranking of different modelling techniques for prediction of site index in Mediterranean mountain forests, Ecol Model 221: 1119-1130. http://dx.doi.org/10.1016/j.ecolmodel.2010.01.007.

Breiman L, Friedman JH, Olshen RA, Stone CJ, 1984. Clas-sification and Regression Trees. Wadsworth & Brooks/Cole Advanced Books & Software. Monterey, C, 358.

Chavez JR, Pat S, 1996. Image-based atmospheric correc-tions-revisited and improved. Photogramm Eng Rem S 62: 1025-1036.

Cohen WB, Spies TA, 1992. Estimation structural attributes of Douglas fir/western hemlock Forests stand from Land-sat and Spot imagery, Rem Sens Envi 41: 1-17. http://dx.doi.org/10.1016/0034-4257(92)90056-P.

Cooke WH, Jacobs DM, 2005. Rapid classification of Land-sat TM imagery for phase stratification using the auto-mated NDVI threshold supervised classification (ANTSC) methodology. In: Proceedings of the fourth annual forest inventory and analysis symposium, 2002 November 19-21, New Orleans, LA. Gen. Tech. Rep. NC-252. St. Paul, MN: US Department of Agriculture, Forest Service, North Central Research Station, 81-86.

Cutler DR, Edwards TC, Beard KH, Cutler A, Hess KT, Gibson J, Lawler JJ, 2007. Random forests for classifica-tion in ecology. Ecology 88: 2783-2792. http://dx.doi.org/10.1890/07-0539.1.

Fazakas Z, Nilsson M, Olsson H, 1999. Regional forest bio-mass and wood volume estimation using satellite data and ancillary data. Agri For Met 98: 417-425. http://dx.doi.org/10.1016/S0168-1923(99)00112-4.

Franco-Lopez H, Ek AR, Bauer ME, 2001. Estimation and mapping of forest stand density, volume, and cover type using the k-nearest neighbour's method. Rem Sen Env 77: 251-274. http://dx.doi.org/10.1016/S0034-4257(01)00209-7.

Freitas SR, Mello MCS, Cruz CBM, 2005. Relationships between forest structure and vegetation indices in Atlantic Rainforest. For Ecol Manage 218: 353-362.

Gebreslasie MT, Ahmed FB, Jan AN, Adrdt V, 2010. Predicting forest structural attributes using ancillary data and ASTER satellite data. Int J App Ear Obs Geoin 125: 523-526. http://dx.doi.org/10.1016/j.jag.2009.11.006.

Hall RJ, Skakun RS, Arsenault EJ, Case BS, 2006. Modelling forest stand structure attributes using Landsat ETM+ data: application to mapping of aboveground biomass and stand volume. For Ecol Manage 225: 375-390.

Huang X, Jensen J, 1997. A Machine- Learning Approach to Automated Knowledge-Base Building for Remote sensing Image Analysis with GIS Data. Photogram Eng Rem Sen 63: 1185-1194.

Huiyan G, Limin D, Gang W, Dong X, Shunzhong W, Hui W, 2006. Estimation of forest volumes by integrating Landsat TM imagery and forest inventory data. Science in China Series E. Tec Sci 49: 54-62.

Hyvonen P, 2002. Kuvioittaisten puustotunnsteja toimenpide-ehdotusten estimointi k-kuviotason tukianeiston Avulla. Metsat Aikaka 3: 363-379.

Hyyppa J, Hyyppa H, Inkinen M, Engdahi M, Linko S, Zhu YH, 2000. Accuracy comparison of various remote sensing data sources in the retrieval of stand attributes. For Ecol Manage 128: 109-120.

Kalbi S, 2011. Estimation of Forest Structural Attributes Using ASTER and SPOT-HRG Data (Case study: Darabkola forest). M. Sc thesis, Department of Forestry, Sari University of Agricultural Sciences & Natural Resources, 107 pp.

Kalbi S, Fallah A, Shataee Sh, 2014. Estimation of forest attributes in the Hyrcanian forests, comparison of advanced space-borne thermal emission and reflection radiometer and satellite poure I'observation de la terre-high resolution grounding data by multiple linear, and classification and regression tree regression models. J App Rem S 8: 2-18. http://dx.doi.org/10.1117/1.jrs.8.083632.

Kilpelainen P, and Tokola T, 1999. Gain to be achieved from stand delineation in Landsat TM image-based estimation of stand volume. For Ecol Manage 124: 105-111.

Lawrence L, Wright A, 2001. Rule-Based Classification and Regression Tree (CART) Analysis. Photogramm Eng Rem Sen 67: 1137-1142.

Makela H, Pekkarine A, 2004. Estimation of forest stands volumes by Landsat TM imagery and stand- Level field-inventory data. For Manage 196: 245-255.

Mohammadi J, Shataee Sh, Babanezhad M, 2011. Estimation of forest stand volume, tree density and biodiversity using Landsat-ETM+ Data, comparison of linear and regression tree analyses. First Conference on Spatial Statistics. Proced Env Sci 7: 299-304.

Mohammadi J, Shataee Sh, Yaghmaee F, Mahiny AS, 2010. Modelling Forest Stand volume and Tree Density Using Landsat ETM+ Data. Int J Remote Sens 31: 2959-2975. http://dx.doi.org/10.1080/01431160903140811.

Moisen GG, Frescino TS, 2002. Comparing five modelling techniques for predicting forest characteristics. Ecol Mod 157: 209-225. http://dx.doi.org/10.1016/S0304-3800(02)00197-7.

Muukkonen P, Heiskanen J, 2005. Estimation biomass for boreal forests using ASTER satellite data combined with stand wise forest inventory data. Remote Sen Env 99: 434-447. http://dx.doi.org/10.1016/j.rse.2005.09.011.

R Core Team, 2012. R: A language and environment for statistical computing R Foundation for Statistical Computing, Vienna, Austria: Available: http://www.R-project.org/.

Sarunas, R. 1997. On dimensionality, sample size, and classification error of nonparametric linear classification algorithms. IEEE Trans. Pattern Anal Mach Intel 19: 667-671. http://dx.doi.org/10.1109/34.601254.

Shataee Sh, Kalbi S, Fallah A, Pelz DR, 2012. Forest attributes imputation using machine-learning methods and ASTER data: comparison of k-NN, SVR, and random forest regression algorithms. Int J Rem Sen 33: 6254-6280. http://dx.doi.org/10.1080/01431161.2012.682661.

Sironen S, Kangas A, Maltamo M, 2010. Comparison of different non-parametric growth imputation methods in the presence of correlated observations. Forestry 83(1): 39-51. http://dx.doi.org/10.1093/forestry/cpp030.

Sivanpillai R, Smith CT, Srinivasan R, Messina MG, BenWU X, 2006. Estimation of managed loblolly pine stands age and density with Landsat ETM+ data. For Manage 223: 247-254.

Tokola T, Heikikkila J, 1997. Improving Satellite image based forest inventory by using a priori site quality information. Silva Fen 31: 67-78. http://dx.doi.org/10.14214/sf.a8511.

Trotter CM, Dymond JR, Goulding CJ, 1997. Estimation of timber volume in a coniferous plantation forest using Landsat TM. Int J Rem Sens 18: 2209-2223. http://dx.doi.org/10.1080/014311697217846.

Tuominen S, Haakana M, 2005. Landsat TM Imagery and High Altitude Aerial Photographs in Estimation of Forest Characteristics, Silva Fen 39: 573-584. http://dx.doi.org/10.14214/sf.367.

Wang YH, Raulier F, Ung CH, 2005. Evaluation of spatial predictions of site index obtained by parametric and non-parametric methods a case study of Lodgepole Pine productivity. For Ecol Manage 214: 201-211.

Wolter TP, Townsend PA, Sturtevant BR, 2009. Estimation of forest structural parameters using 5 and 10 meter SPOT-5 satellite data. Rem Sens 113: 2019-2036. http://dx.doi.org/10.1016/j.rse.2009.05.009.

Yazdani S, 2011. Estimation of Forest Structural Attributes Using Quickbird Data. M. Sc thesis, Department of Forestry, Gorgan University of Agricultural Sciences & Natural Resources, 156.