ESTIMATION OF FOREST STAND PARAMETERS BY USING THE SPECTRAL AND TEXTURAL FEATURES DERIVED FROM DIGITAL AERIAL IMAGES

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Abstract. Remote sensing data are important data sources in the management and planning of forest ecosystems. In this study, we aimed to estimate forest stand parameters using the spectral (*Average Brightness Value*) and textural features (*Standard Deviation of Gray Levels, Entropy, Contrast, Correlation, Homogeneity*) derived from digital aerial images. Study was carried out in Adıyaman Forestry Operation Directorate in Turkey. Relationships between image features and stand parameters (diameter at breast height-DBH, mean height, stand volume, basal area, and number of trees) were tested by using Pearson's correlation coefficient. Image features exhibiting the highest correlation with stand parameters were modelled by a linear regression analysis. The validity of the models developed was then tested using the leave-one-out cross-validation method. The '*Contrast*' values derived from the infrared band showed the highest correlation with DBH and mean height, the '*Contrast*' values from the red band showed the highest correlation with stand volume and basal area, and the '*Homogeneity*' values from the infrared band showed the highest correlation with the number of trees. The adjusted coefficients of determination (R^2_{adj}) of the estimation models were calculated 0.48 for DBH, 0.38 for mean height, 0.41 for stand volume, 0.45 for basal area and 0.43 for tree number. The relative root mean square error (RMSE%) values were for each parameters 11.91%, 23.57%, 20.96%, 15.81% and 16.20%, respectively.
Keywords: *forest inventory, remote sensing, digital aerial image, forest properties, image features*

Introduction

Effective management and planning of forest ecosystems requires up-to-date and reliable data. Remote sensing data have great potential as an auxiliary data source in estimating forest structural variables (Kayitakire et al., 2006). Forest inventory for forest management planning is traditionally based on the combination of field measurement and aerial photographs. In this method, forest stands are delineated on the basis of aerial photographs and forest stand parameters (e.g. volume, basal area, density) are calculated using some empirical formulas after necessary measures on the sample plots. Aerial photographs are widely used in mapping forest stands. However, as this approach usually necessitates visual photo interpretation, its success depends on the experience of interpreter. Therefore, it is time-consuming and subjective particularly on large areas (Gong et al., 1999; Tuominen and Pekkarinen, 2005; Morgan and Gergel, 2013; Balenovic et al., 2015). Moreover, field measurements are the most widely used data source in forest inventory. Periodical field measurements yield the most accurate results. Nevertheless, its cost, time-consuming and labour-intensive nature removes these advantages (Müllerová, 2005; Gonzalez-Benecke et al., 2014).

Apart from these disadvantages of traditional methods, improvements in computer technologies and satellite images have caused a gradual transition from traditional methods to semi-automatic and automatic methods (Hájek, 2008; Balenovic et al.,

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2015). Multispectral remote sensing images produce reliable digital data for the automatic estimation of forest stand parameters. Automatic image analysis techniques also provide a rapid estimation of the forest stand parameters through these images (Hayitakire et al., 2006; Huang et al., 2013). Taking advantage of satellite image data in forest inventory has increased interest since the first satellite of LANDSAT program launched in 1972. With the advances in technology, the production of sensors which provide high resolution and multispectral image has raised more interest (Franco-Lopez et al., 2001; Katila et al., 2001). Several studies carried out so far have focused on using multispectral satellite images such as Landsat, SPOT, IKONOS, QuickBird and WorldView to estimate forest stand parameters. For instance, Hyyppä et al. (2000) evaluated SPOT XS, SPOT Pan and Landsat TM satellite images in terms of the estimation accuracy of stand volume, mean tree height and basal area. Ozkan (2006) investigated the possibilities of estimating the forest stand parameters (number of trees, stand volume, basal area, mean diameter and mean height) with the spectral features derived from SPOT-5 satellite data. In another study carried out by Kayitakire et al. (2006), the estimation capabilities of IKONOS satellite image in spruce forest stands for five main forest variables (age, top height, circumference, stand density and basal area) was evaluated. Hall et al. (2006) developed a forest stand volume model using the relation between forest structural features and spectral features from Landsat ETM+ image. Similarly, Ozdemir and Karnieli (2011) evaluated the determination of forest structural parameters using image textural features derived from WorldView-2 satellite image. The obtained results indicated that satellite images can be used for the estimation of forest structural features on large areas. However, the accuracy of estimations models failed to satisfy at sample plot or forest stand level. Therefore, their suitability is thought to be low in forest management planning studies.

Recent studies have focused on estimating forest stand parameters using digital aerial images due to the less accuracy of satellite images (Kayitakire et al., 2006; Balenovic et al., 2015). Aerial photographs are an important data source for sample plot or forest stand level forest inventory (Morgan et al., 2010). Over the last 30 years, there has been a transition from analogous photogrammetry to digital photogrammetry as analogous aerial photographs are replaced with digital aerial images (Balenovic et al., 2015). In addition to high spatial resolution, RGBIR (Red, Green, Blue, Infrared) bands and digital data flow of digital aerial images provide a great advantage in estimating forest stand parameters and producing forest stand maps (Hájek, 2008). While some of the forest stand parameters (such as tree height, crown diameter, crown closure) can be measured directly from digital images, some others can be calculated using empirical formulas or estimated using image features. For the estimation of forest stand parameters, spectral and textural properties of remote sensed images are the most important characteristics (Zhou and Sun, 1995; Mäkinen et al., 2006; Ozdemir and Karnieli, 2011).

In addition to image spectral features, textural features can also be calculated through original pixel values. The spectral features can be defined as average reflection value of an image window (Anttila, 2005). ‘first-order texture’ which includes statistical variation measurements and ‘second-order texture’ which includes *Grey Level Co-occurence Matrix (GLCM)* proposed by Haralick et al. (1973) are the most widely used textural features of digital images to define (Ozdemir et al., 2008; Ozdemir and Donoghue, 2013). Recently, *GLCM* Textural features have been widely used (Levesque and King, 2003; Coburn and Roberts, 2004; Tuominen and Pekkarinen, 2005;

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Kayitakire et al., 2006; Maltamo et al., 2006; Hájek, 2008; Ozdemir and Karnieli, 2011; Tuominen and Haapanen, 2011; Sarker et al., 2012; Ozdemir et al., 2012; Ozdemir and Donoghue, 2013; Ozkan, 2014; Walner et al., 2014; Lu et al., 2016; Ozkan et al., 2016; Ozkan et al., 2017). Nevertheless, these studies are mostly carried out using satellite images. It is stated that the textural features can be an important explanatory variable to estimate the stand parameters from high-spatial resolution images such as digital aerial images. And also textural features as well as spectral features can improve the estimation accuracy (Tuominen and Pekkarinen, 2005; Anttila, 2005; Packalén, 2009). Nevertheless, estimation of forest stand parameters using spectral and textural features of digital aerial images has not been studied adequately. Further studies are still necessary for operational using of spectral and textural features in forest management planning.

Effective use of digital aerial images in forest management planning relies on the relation between the scale of target object (tree, forest stand, etc.) and spatial resolution of digital aerial image (Falkowski et al., 2009). Target objects are much larger than image pixel size and a single pixel does not contain significant data when considering target objects. Therefore, related parameter should be extracted from a larger area than a single pixel. For example, although forest stand is defined as a homogenous area in forest management practice, forest stand is not an entirely homogenous object in terms of image features. Forest stands in remote sensed images comprise of a composition of various spectral classes such as small gaps, shadowy and sunny crown. Object-based image analysis is considered as an important approach for extracting significant information from high spatial resolution remote sensed images (Antunes et al., 2003; Huang et al., 2013). On forest stand level, image segmentation which is the first step in object-based image analysis, is a useful algorithm that increase accuracy of forest stand parameters estimation (Anttila, 2005).

The purpose of this study is to predict forest stand parameters using the spectral and textural features derived from digital aerial image. To achieve this goal, firstly, the relations between forest stand parameters and image features were analyzed and investigated to determine which one of them are suitable options for estimation models. Then, linear regression analysis utilized for estimation models with considering image features and also validity of the models were tested using adjusted coefficient of determination (R^2_{adj}), root mean square error (RMSE) and relative root mean square error (RMSE%).

Materials and methods

Study area

Study area is located between 37°59’29”–37°24’02” north latitude and 38°31’30”–37°25’44” east longitude in Şanlıurfa Regional Directorate of Forestry, Adıyaman Forestry Operation Directorate in Turkey (*Figure 1*). The study area covers 439621 hectares which general land comprise of 105771 hectare forested land. Dominant tree species of study area is Brutian pine (*Pinus brutia Ten.*) and Oak (*Quercus brantii var. persica, Quercus libani var. angustifolia, Quercus infectoria var. boissieri, Quercus cerris var. variegata*). Besides these, Juniper (*Juniperus excelsa var. excelsa, Juniperus oxycedrus var. oxycedrus*) species are found at high altitude areas. Oak stands are managed as coppice and juniper stands are located fragmentary. This study covers Brutian pine plantations.

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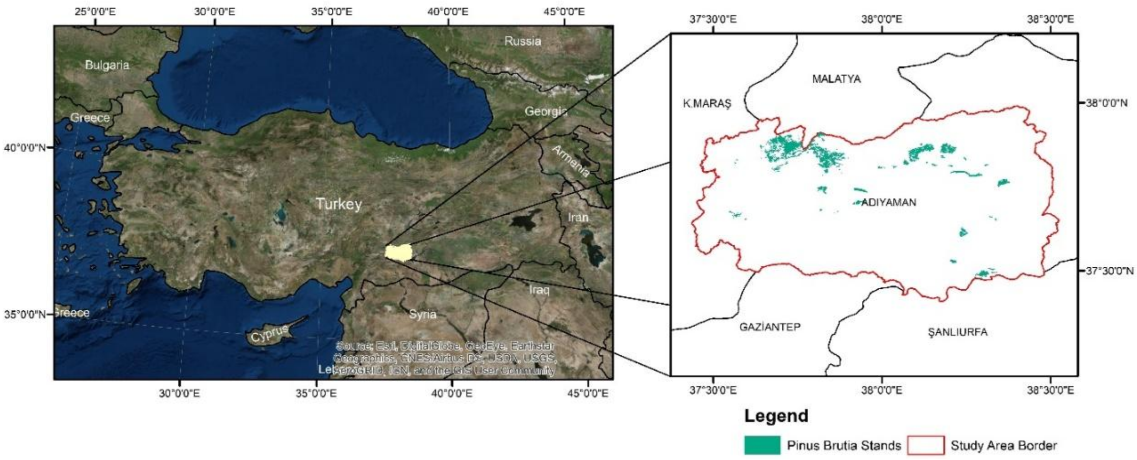

Figure 1. *Geographical location of study area*

Digital aerial imagery

Aerial images used in the study are totally comprised of four bands which are Red (580-700 nm), Green (480-630 nm), Blue (410-540 nm) and Infrared (690-1000 nm) bands. These images are taken as stereo from altitude of 7200 meters, 70 % forward and 30 % side overlap, by airborne using UltraCamX (Microsoft, Vexcel Imaging GmbH) digital aerial camera which has 7.2 µm physical pixel size, in 2011. For each stereo image pair, geometric calibration and radiometric correction utilized in ERDAS LPS (Hexagon Geospatial) software using interior (focal length, coordinates of the principal point) and exterior (position and rotation of the camera) orientation parameters of raw images.

Vegetation indexes were developed using the original bands in order to provide more detailed data concerning the areas covered with vegetation in multi-channel images, (Jensen and Lulla, 1987). In the present study, 3 vegetation indexes (Difference Vegetation Index-DVI; Infrared Percentage Vegetation Index-IPVI; Normalized Difference Vegetation Index-NDVI) were used (*Table 1*).

Table 1. *Vegetation indexes used in the study*

Vegetation index	Equation	Author
DVI	$NIR - RED$	Tucker 1979
IPVI	$\frac{NIR}{NIR + RED}$	Crippen 1990
NDVI	$\frac{NIR - RED}{NIR + RED}$	Rouse et al. 1974

Besides, Principal Component Analysis (PCA) was applied to digital image in order to form a new data group including more information (Jensen and Lulla, 1987) by pushing similar channels. PCA can be repeated more than once with the purpose of increasing

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detail, new data group which are produced in this way are also named as PC1, PC2. However, many studies have indicated that PC1 involves the most details for remote sensing data (Sena et al., 2002; Çam et al., 2015). PCA image, vegetation indexes and original bands used in the study are shown in *Figure 2*.

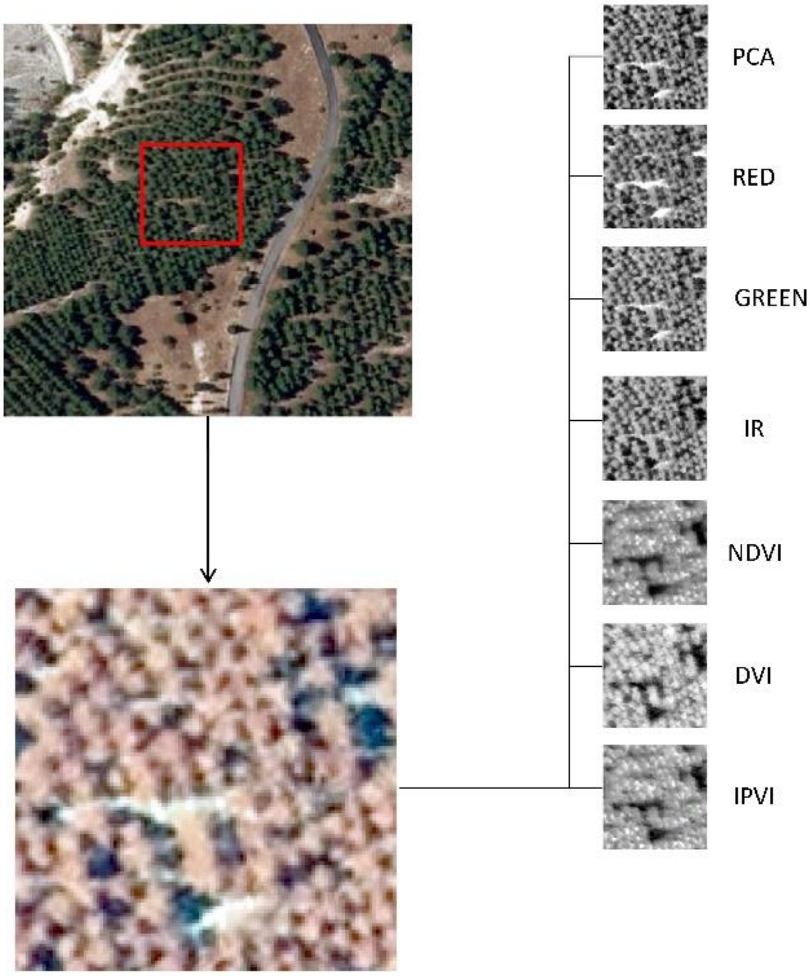

Figure 2. *Original bands, vegetation indexes and PCA image*

Field data

Field data were used with the purpose of revealing the relation between forest stand parameters and image features. Fieldwork was carried out in sampling clusters of four plots which had size of 50 x 50 m during July-August 2013. Sampling clusters, as 20 items in total, were randomly chosen from image objects formed with image segmentation process. Sample plots in sampling clusters were located as 50 m distance from the center to center. The centers of sample plots were located with the distance of 25 m from the center of sampling clusters to North, South, East and West directions. Sample plots were established as 400 or 600 m^2 circle (*Figure 3*).

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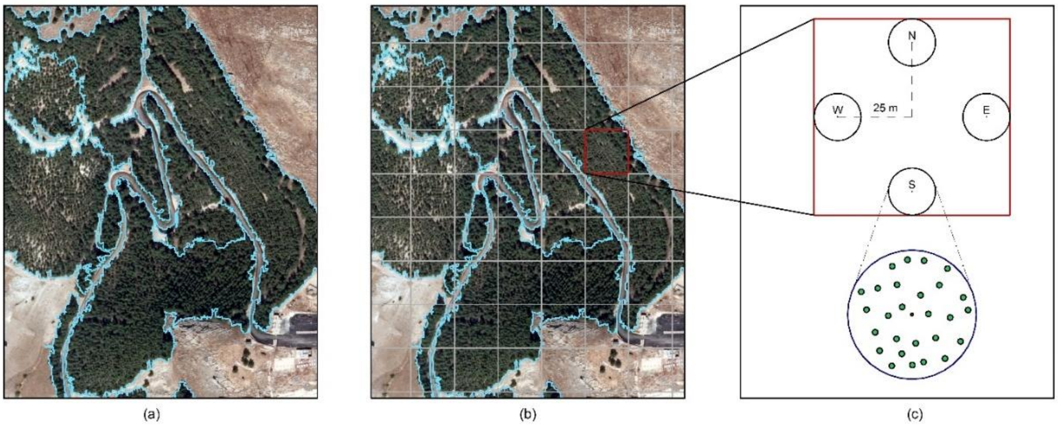

Figure 3. *a) Multi-resolution segmentation b) Chessboard segmentation c) Sample plots*

The size of sample plots were determined considering stand development age and crown closure. The measurements were carried out considering conventional forest inventory rules in totally 80 sample plots. Diameter of all trees inside the sample plot with the diameter at breast height (DBH) more than 8 cm, the height (m) and age according to the %40 rule were measured. Stand volume (m^3/ha), basal area (m^2/ha), number of trees (stems/ha), DBH (cm) and mean height (m) of each sample plot were calculated using the equations given in *Table 2*. For sampling clusters, forest stand parameters per hectare were determined as the average of (4) sample plots in each sampling cluster. Descriptive statistics related to forest stand parameters determined with field measurements are presented in *Table 3*.

Table 2. *Equations to calculate forest stand parameters*

Stand parameters	Equation	Author
Volume	$\ln V = \ln a_1 + a_2 \ln d_{1.3} + a_3 \ln h$ $* \; a_1 = -2.077466 \quad a_2 = 1.676818 \quad a_3 = 0.845096$	Usta (1991)
DBH	$d_g = \sqrt{\frac{4*G}{\pi * N}}$	Husch et al. (1993)
Basal Area	$BA = \frac{\pi}{4} \sum d_{1.3}{}^2$	Kalıpsız (1999)
Mean Height	$h = h_{weise}$	Kalıpsız (1999)

*where $d_{1.3}$ were diamater at breast height, G were basal area in cm^2, N were number of trees per hectare, h were height of tree

Table 3. *Descriptive statistics of ground measurement data*

	DBH (cm)	Mean height (m)	Stand volume (m^3/ha)	Basal area (m^2/ha)	Number of trees (stems/ha)
Mean value	16.92	8.16	45.55	10.39	487.63
Minimum value	13.14	4.35	24.36	6.51	345.75
Maximum value	21.77	12.70	70.23	15.28	681.25
Standart deviation	2.65	1.93	11.93	2.14	99.74

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Image segmentation

Sampling clusters obtained by image segmentation are stated to be a better estimation unit than sample plots (Anttila, 2005; Hyvönen et al., 2005). The segmentation is an algorithm which creates meaningful objects in an image by grouping the individual pixels according to their spatial and spectral features and is performed using the scale parameter and homogeneity criteria (Benz et al., 2004). The main objective of this process is to obtain more meaningful sub-objects from the heterogeneous structure of images (Blaschke et al., 2014; Li et al., 2015). A number of segmentation techniques have been developed (Definiens, 2006). In this study, image segments were firstly obtained from digital aerial image by using Multi-resolution Segmentation algorithm on forest stand level. For this purpose, the image segmentation process was implemented by testing different scale and color/shape parameters which represents the forest stands in the study area. As a result of visual evaluations, the most suitable image objects were obtained by using scale parameter: 175, color: 0.7 and shape: 0.3. Then, chessboard segmentation approach was implemented to achieve image windows representing ground sampling clusters into the obtained image objects. In this way, the size of image objects was segmented into 50 x 50 m cells (*Figure 3*).

Extraction of the image features

In the study, spectral and textural features of digital aerial image were used for the estimation of forest stand parameters (*Table 4*).

Table 4. *Image features used in the study*

Image Features		Relationship model*
Average brightness value		$\frac{1}{\#P_v}\sum_{(x,y)\in P} C_k(x,y)$
First-order	*Standard Deviation of Gray Levels*	$\boldsymbol{\sigma_k}(v) \coloneqq \boldsymbol{\sigma_k}(\boldsymbol{P_v}) = \sqrt{\frac{1}{\#P_v}\left(\sum_{(x,y)\in P} c_k^2(x,y) - \frac{1}{\#P_v}\sum_{(x,y)\in P} C_k(x,y)\sum_{(x,y)\in P} C_k(x,y)\right)}$
Second-order	*GLCM Contrast*	$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$
	GLCM Entropy	$\sum_{i,j=0}^{N-1} P_{i,j}(-lnP_{i,j})$
	GLCM Correlation	$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right]$
	GLCM Homogeneity	$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$

*Parameters (Definiens 2006)
i is the row number, j is the column number, P_v is the cluster of pixels of the image object, # P_v is the total number of current pixels in P_v, (x,y) is the coordinates of pixels, $c_k(x,y)$ is the pixel value, Pi,j is the normalized value in the cell i, j, N is the number of columns and rows, μi and μj represent the average of the row i and column j, σi and σj represent the standard deviation of the row i and column j

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Average Brightness Value (ABV) of pixels in an image window corresponding sampling clusters was taken into consideration as spectral property. The first-order (*Standard Deviation of Gray Levels-SDGL*) and second-order texture features were used as textural features as well. The first-order texture features are calculated using statistical properties of pixel brightness values in an image area. Furthermore, the second-order texture features are calculated based on *Grey Level Co-occurence Matrix (GLCM)*. *GLCM* is a tabulation of how often different combinations of pixel grey levels occur in an image object (Harralick et al., 1973). According to *GLCM*, many textural features can be determined which are categorized in three main groups as *Contrast, Orderliness* and *Descriptive statistics* (Ozdemir and Karnieli, 2011). *Homogeneity (HOM), Contrast (CON), Correlation (COR) and Entropy (ENT)*, which habe been used widely in previous studies, were chosen to be used in the current study. Image features were derived from 3 digital bands (R, G, NIR), PCA and 3 vegetation indexes (NDVI, DVI, IPVI). Image features were extracted from image objects which segmented into 50 x 50 m cells by Definiens image processing software

Statistical analysis

SPSS 16 (SPSS Chicago, IL, USA) statistical software was used to perform statistical analysis. Pearson Correlation analysis was used for the determining the statistical relation between forest stand parameters and image features. Pearson correlation coefficient can be used in the cases in which the data have a normal or near-normal distribution. The normality of the distribution of the variables were tested based on Shapiro-Wilk method. Variable was regarded as having normal distribution when $P>0.05$ (Kalaycı, 2006; Kayitakire et al., 2006).

The linear regression analysis was utilized to develop forest stand parameter estimation models, using image features derived from the digital aerial image. Forest stand parameters which were calculated based on field measurements were considered as dependent variable and image features which were derived from image windows were considered as independent variable in the regression analysis. In the regression analysis, one of the important issues is the variable choice when there are a large amount of predictor variables (Shinzato et al., 2016). For choising the proper variable, the highest correlation coefficient between forest stand parameters and image features was considered. By Kayitakire et al. (2006) a simple linear model of the form $y = b_0 + b_1x$ has been proposed to present a simple and interpretable model, emphasizing that there are no theoretical functional forms for the forest variable estimation models using textural features.y refers to forest stand parameters, x refers to image features, b_0 and b_1 refer to coefficients of the model. In the present study, this approach was adopted to model relation between forest stand parameters and image features. Each forest stand parameter was evaluated separately and a different model was developed for each one. Then, the validity of the estimation models was tested using the leave-one-out cross-validation test. In this method, one sampling cluster from dataset was eliminated and a model was developed using left sampling cluster. The forest parameters of eliminated sampling cluster were predicted according to the model that was not include leaved out. The predicted values for 20 sampling clusters were obtained by repeating the same process for each sampling clusters. Then, the adjusted coefficient of determination (R^2_{adj}), the root mean square error (RMSE) and the relative root mean square error (RMSE%) values were calculated by comparing predicted values with ground truth data.

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Results

Correlation analysis

Data should exhibit a normal distribution to reveal the direction and power of a linear relationship between image features and forest stand parameters by performing a correlation analysis. According to the normal distribution test conducted, it was determined that the all forest stand parameters obtained from field measurements in the sample plots exhibited a normal distribution. Following the normal distribution test, a relationship between the image features and forest stand parameters was evaluated by Pearson's correlation coefficient.

As a result of the evaluation performed, statistically significant relationships were found between DBH, mean height, stand volume, basal area, and the number of trees calculated based on the sampling clusters and brightness and textural features derived from a digital aerial image. The relationships between the forest stand parameters and image features are presented in *Table 5*.

Table 5. *Pearson correlation coefficients between image features and forest stand parameters (best correlation)*

	DBH	Mean height	Stand volume	Basal area	Number of tree
a) Correlation coefficients between stand parameters and image features derived from infrared band					
ABV	-0.196	-0,056	-0,071	-0,059	0,285
SDGL	-0,065	-0,007	-0,044	0,164	0,234
HOM	0,658**	0,506**	0,442	0,431	-0,679**
CON	-0,708**	-0,641**	-0,524*	-0,508*	0,668**
COR	0.690**	0,627**	0,558*	0,578**	-0,577**
ENT	-0.030	-0,088	-0,136	-0,112	0,010
b) Correlation coefficients between stand parameters and image features derived from red band					
ABV	-0,221	-0,154	-0,126	-0,092	0,245
SDGL	-0,427	-0,373	-0,401	-0,276	0,314
HOM	0,641**	0,631**	0,637**	0,643**	-0,455
CON	-0,604**	-0,626	-0,663**	-0,692**	0,322
COR	0,535*	0,597*	0,600**	0,648**	-0,322
ENT	-0,163	-0,096	-0,082	-0,032	0,247
d) Correlation coefficients between stand parameters and image features derived from DVI					
ABV	-0,002	0,122	0,062	-0,033	0,097
SDGL	-0,381	-0,397	-0,393	-0,315	0,179
HOM	0,364	0,384	0,354	0,388	-0,253
CON	-0,322	-0,307	-0,394	-0,432	0,161
COR	0,301	0,282	0,369	0,411	-0,152
ENT	-0,393	-0,451*	-0,452*	-0,459*	0,248
d) Correlation coefficients between stand parameters and image features derived from PCA					
ABV	-0,277	-0,182	-0,153	-0,113	0,320
SDGL	0,064	-0,005	0,030	0,108	0,013
HOM	0,636**	0,591**	0,492*	0,508*	-0,567**
CON	-0,607**	-0,650**	-0,612**	-0,652**	0,398
COR	0,600**	0,634**	0,605**	0,652**	-0,387
ENT	-0,654**	-0,612	-0,568**	-0,565**	0,519*

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

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The relevant table shows the image features having the best correlation with the forest stand parameters. In summary, the highest correlation between DBH and image features was obtained with the *CON* values derived from the infrared band (r=0.708, p<0.01). A significant and negative correlation was found between the *CON* value derived from the red band and DBH (r=0.604, p<0.01). A significant and positive correlation was observed between the *HOM*, *COR* values derived from the red and infrared bands and DBH (r=0.641, 0.535 and 0.58, 0.690 p<0.01, respectively). Besides, significant relationships were determined between the *CON*, *HOM*, *COR*, and *ENT* values derived from PCA and DBH. In addition to these, relationships between other textural features and brightness values and DBH were generally weak. The highest correlation between the mean height and the image features was also calculated with the *CON* values derived from the infrared band (r=0.641, p<0.01). While significant relationships were observed between the *HOM*, *CON*, *COR* values derived from the red band and the *CON*, *ENT*, *COR* values derived from PCA and the mean height, the relationships between the mean height and other image features (*ABV* and *SDGL*) were generally weak.

Significant correlations were also calculated between the stand volume and some textural features. On the other hand, it was observed that relationships between the stand volume and brightness values were weak. The highest correlation with the stand volume was calculated with the *CON* values derived from the red band (r=0.663, p<0.01). Furthermore, stand volume had significant positive relationships with the *HOM*, *COR* values and significant negative relationships with *CON*, *ENT* values derived from red band, infrared band and PCA. Similarly, while the basal area exhibited significant correlations with some textural features, exhibited a weak correlation with brightness values. The highest correlation for the basal area was obtained with the *CON* values derived from the red band (r=0.692, p<0.01). The highest correlation in the number of trees was obtained with the *HOM* values derived from the infrared band (r=0.679, p<0.01). Moreover, it was determined that there was a significant and positive correlation between the number of trees and the *CON* values derived from the infrared band and the *ENT* values derived from PCA (r=0.668, 0.519, p<0.01). Apart from these, it was understood that the relationships between the *ABV, SDGL, COR* values and the number of trees were generally weak.

Estimation of forest stand parameters

In order to estimate the forest stand parameters based on the image features, the relationship between the forest stand parameters and the image features was modeled by a linear regression analysis. According to the results of the correlation analysis, various textural features exhibited a statistically significant correlation with the forest stand parameters. The image features to be used as independent variables of the model were selected from those having the highest correlation with the forest stand parameters. Accordingly, the *CON* values derived from the infrared band were modeled as the best indicators of DBH and mean height. The *CON* values derived from the red band were the independent variables of the model as the best indicators of the forest stand volume and basal area. The *HOM* values derived from the infrared band were used as independent variables of the model estimating the number of trees. The accuracy of the estimates provided by the regression models was explained by the R^2_{adj}, RMSE, and RMSE% values. The R^2_{adj}, RMSE, and RMSE% values related to the regression models developed for each forest stand parameter and the estimates obtained from the models are presented in *Table 6*.

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As seen from *Table 6*, the model coefficients were found as statistically significant ($p<0.001$) in the models developed to estimate DBH, mean height, stand volume, basal area, and the number of trees. Upon evaluating the results, it was found out that the model providing the highest estimation accuracy among the estimation models was the model developed to estimate DBH. The adjusted coefficient of determination (R^2_{adj}) of the relevant model was calculated to be 0.48. Accordingly, the linear regression model, in which the *CON* values derived from the infrared band were used as independent variables, estimated 48% of the change in DBH. In terms of the estimation accuracy, this model was followed by estimation models developed to calculate the basal area, number of trees, and stand volume. The estimation accuracy of the model developed for the mean height was relatively low compared to the others. The R^2_{adj} values of these models calculated using all datasets were found to be 0.45, 0.43, 0.41 and 0.38, respectively. Upon comparing the DBH values estimated from the model with the ground truth DBH values, RMSE was calculated to be 2.02 cm (RMSE 11.91%). Similarly, upon comparing the other stand parameters estimated from the developed models with the ground truth data, RMSE was calculated to be 1.92 m for the mean height, 9.55 m^3/ha for the stand volume, 1.64 m^2/ha for the basal area, and 79.01 stems/ha for the number of trees. RMSE% was found to be 23.57% for the mean height, 20.96% for the stand volume, 15.81% for the basal area, and 16.20% for the number of trees.

Table 6. *Estimation models based on image textural features of forest stand parameters and their statistical summaries*

Stand parameters	Estimation model	R^2_{adj}	RMSE	%RMSE	p-value
DBH	25.296-0.017**CON*_IR	0.48	2.02	11.91	0.000
Mean height	14.658-0.013**CON*_IR	0.38	1.92	23.57	0.002
Stand volume	71.986-0.064**CON*_RED	0.41	9.55	20.96	0.001
Basal area	15.334-0.012**CON*_RED	0.45	1.64	15.81	0.001
Tree number	834.271-4965.119**HOM*_IR	0.43	79.01	16.20	0.001

Discussion

Our study goal was to reveal the potential of spectral and textural features derived from digital aerial image in predicting forest stand parameters. The results of correlation analysis revealed that there were statistically significant correlations especially between the image textural features and forest stand parameters. DBH, among the forest stand parameters, exhibited the highest correlation with the *CON* values derived from the infrared band ($r=0.708$, $p<0.01$). Furthermore, significant correlations were observed between some textural features (*CON, HOM, COR, ENT*) derived from the red, infrared bands, and PCA, and the DBH. Again, while there were significant correlations between the textural features such as *CON*, *HOM*, *COR*, and *ENT* with the mean height, the highest correlation was obtained with the mean height and the *CON* values derived from the infrared band ($r=0.641$, $p<0.01$). Significant correlations were observed between the stand volume and basal area and some textural features. The highest correlation with the stand volume and the basal area was achieved with the *CON* values derived from the red band ($r=0.663$, 0.692, $p<0.01$). While the number of trees had significant correlations with the textural features such as *HOM*, *CON*, and *ENT*, it exhibited the highest correlation with the *HOM* values derived from the infrared band ($r=0.679$, $p<0.01$).

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According to these results, while the correlations between *ABV* and *SDG*L derived from the digital image and forest stand parameters were generally weak, *GLCM* textural features gave the best results for the estimation of the forest stand parameters. Therefore, based on the correlation coefficient values, the *CON* property derived from the infrared band was the best indicator in the estimation of DBH and mean height parameters. While the *CON* property derived from the red band was the best indicator in the estimation of the stand volume and basal area, the *HOM* property derived from the infrared band was the most appropriate indicator in the estimation of the number of trees. Furthermore, it was revealed that the original bands of the digital aerial image (RED, IR) were more appropriate than vegetation indexes and PCA for the estimation. Significant differences were also found between the vegetation indexes and PCA. PCA was found to have a better correlation with the forest stand parameters than the vegetation indexes.

The results of our study are consistent with the relevant literature. For example, in the study conducted by Tuominen and Pekkarinen (2005), the estimation accuracy of the forest properties (DBH, height, basal area, and volume) was examined by using the spectral and textural features derived from the digital aerial image. As a result of the study, textural features generally exhibited higher correlations with forest properties than spectral features. Again in the same study, differently from the present study, image features derived from the original image bands generally exhibited a weaker correlation with forest properties. Kayitakire et al. (2006) evaluated the ability to estimate forest properties based on the textural features of a 1 m resolution IKONOS-2 satellite image. It was stated that there was a very high correlation (R^2= from 0.76 to 0.80) between the top height, circumference, stand density, and age and *GLCM* textural features (*COR* and *CON*). A weak correlation (R^2=0.48) was determined between the basal area and textural features. In a study conducted by Ozdemir et al. (2008) on natural forests using ASTER satellite images, it was determined that there was a significant correlation between the tree size diversity based on the basal area and *HOM*. In a study conducted to estimate the tropical forest properties from a SPOT-5 satellite image using textural features, Castillo-Santiago et al. (2010) revealed that textural features may be a determinant of forest properties. In another study conducted by Ozdemir and Karnieli (2011), it was aimed to estimate the forest structural parameters by using the image textural features derived from a WorldView-2 satellite image. As a result of the study, it was stated that there were significant correlations between the first-order and second-order textural properties and structural parameters. It was expressed that the strongest correlation was calculated between the *CON* derived from the red band and the Standard Deviation of Diameters at Breast Heights (R^2=0.56) and between the *ENT* derived from the blue band and the basal area (R^2=0.53). In a study conducted by Ozkan et al. (2017) in urban forests using Landsat-8, ASTER, and RapidEye satellite images with different resolutions, it was emphasized that image textural features can be a good indicator for evaluating the structural diversity of urban forest stands.

Our results showed that textural features is likely a better indicator than spectral features in estimating stand parameters from digital aerial images. The second-order textural features had more advantageous than first-order textural features. According to the results of the leave-one-out cross-validation analysis, the R^2_{adj} values of the linear regression models developed for the estimation of forest stand parameters varied between 0.38 and 0.48. The DBH and the mean height estimation models developed

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based on the *CON* property derived from the infrared band had 0.48 and 0.38 R^2_{adj}, 2.02 cm and 1.92 m RMSE. The forest stand volume and the basal area models developed using the *CON* property derived from the red band had 0.41 and 0.45 R^2_{adj}, 9.55 m^3/ha and 1.64 m^2/ha RMSE. The estimation model of the number of trees developed based on the *HOM* property derived from the infrared band had 0.43 R^2_{adj}, 79.01 stems/ha RMSE.

Due to the lack of studies on the estimation of forest stand parameters based on textural features from digital aerial images, the results of the present study could not be directly compared with the relevant literature. Therefore, studies in which estimation models were developed based on satellite images were used in the comparison of results. In the study conducted by Tuominen and Pekkarinen (2005), the DBH, height, basal area, and volume were attempted to be estimated by using spectral and textural features (such as *COR, CON, ENT*) derived from color-infrared aerial photographs. In the study in which forest stand parameters were estimated using the k-NN method, the RMSE values of the estimation model based on a single image property were calculated to be 8.54 cm for DBH, 6.69 m for height, 8.40 m^2/ha for basal area, and 78.75 m^3/ha for volume. In the study, it was also stated that the use of textural features improved the estimation accuracy. Kayitakire et al. (2006) modeled the forest stand parameters including the age, top height, circumference, stand density, and basal area using the image textural features derived from 1-m resolution IKONOS-2 imagery. The estimation errors of the models were estimated by using the leave-one-out cross-validation method. In the model in which the *CON* property was used, the R^2 value for the basal area was calculated to be 0.35, and in the model in which the *COR* property was used, the R^2 value for the height was calculated to be 0.76. Wunderle et al. (2007) tried to develop models that best describe forest stand parameters such as the diameter at breast height, height, stem density, and basal area, using the spectral and textural features derived from a pan-sharpened SPOT-5 image. It was emphasized that the first-order (standard deviation) and second-order (correlation) textural features explain the change in forest stand parameters better in the models developed with the stepwise regression analysis. In a study conducted by Ozdemir and Karnieli (2011), forest stand parameters were modelled as the function of textural features derived from the original bands of a WorldView satellite image. The models were developed by using the linear regression analysis. The second-order texture features (*CON* and *ENT*) gave the best result for the DBH, basal area, and stand volume and the first-order texture features (*SDGL*) gave the best result for the number of trees. The R^2 values of the most appropriate model were calculated to be 0.67 for DBH, 0.54 for the basal area, 0.42 for the stand volume, and 0.38 for the number of trees. Wallner et al. (2014) modelled forest stand parameters based on spectral and textural features derived from a RapidEye image. The R^2 values of the developed models were calculated to be in the range of 0.37-0.55 for the mean diameter, 0.40-0.58 for the basal area, 0.30-0.41 for the stem number, and 0.42-0.63 for the volume.

In the literature on the subject, there are mostly studies using spectral features derived from digital aerial images and usually satellite images. In a study conducted by Hyypä et al. (2000), estimation models were developed for the mean height, basal area, and stem volume using aerial images and SPOT PAN. As a result of the study, it was observed that the model based on the aerial image (R^2= 0.34, 0.48, 0.48) provides a higher estimation accuracy than SPOT PAN (R^2= 0.17, 0.38, 0.35). Mallinis et al. (2004) revealed that R^2_{adj} values varied between 0.24-0.31, 0.29-0.32, and 0.20-0.32,

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respectively, in the estimation of volume, basal area, and number of trees with models developed based on the spectral features of a Landsat TM satellite image. Peuhkurinen et al. (2008) reported RMSE values to be 52.2 m^3/ha, 5.6 m^2/ha, and 3.1, respectively, in the estimation of stand volume, basal area, and mean height estimation by using the Ikonos satellite image and k-MSN method. In a study conducted by Günlü et al. (2013), the R^2_{adj} values of the regression models in which the spectral feature derived from a Quickbird satellite image was an independent variable, varied between 0.19 and 0.70 for the forest stand volume. In another study conducted by Günlü et al. (2014), the correlation between spectral features and some forest stand parameters was modeled by using a Pan-Sharpened IKONOS satellite image. The R^2_{adj} values of the best models were determined to be 0.41 for the stand volume, 0.43 for the basal area, and 0.45 for the dominant height. Çil et al. (2015) modelled the tree number, stand volume, and basal area as a function of spectral features derived from Göktürk-2, Rasat, Landsat-8 and the digital aerial image. The R^2_{adj} values of the model developed based on the aerial image were found to be 0.23, 0.48, and 0.55, respectively, for the relevant parameters. The R^2_{adj} values of the model developed based on satellite images varied between 0.34 and 0.67. It was also stated in the study that the original bands gave better results than the vegetation indexes and ratio images.

As a result, the adjusted coefficient of determination values of the estimation models developed for forest stand parameters varied between 0.38 and 0.48 and these values are in line with the literature results. However, these values do not seem to be sufficient in terms of practical forest management. In order for estimation models to be transferred to the practical application, the estimation accuracy should be improved. Therefore, further studies on this subject can evaluate other *GLCM* textural features of the contrast, orderliness, and descriptive statistics groups and models using different image features together can be developed. Another alternative is the combined use of digital aerial images and airborne laser scanning (ALS) data. Studies conducted by Mohammadi et al. (2017) and Jayathunga et al. (2018) revealed promising results for the modeling of forest stand parameters with the combination of digital aerial images and ALS data. Furthermore, the study we conducted was carried out in a conifer plantation forest. The results of the previous studies show differences according to tree species. There is a need for this study to be conducted on different forest types.

Conclusion

The most important result of this study, which was conducted to estimate forest stand parameters based on the spectral and the textural features derived from digital aerial images, is that the second-order texture features gave the best results compared to the spectral and first-order textural features. Among the second-order textural features, '*Contrast*' exhibited better performance than the others. The models developed by using the '*Contrast*' property enabled the better estimation of DBH, mean height, stand volume, and basal area. Nevertheless, the model developed by using the '*Homogeneity*' property allows better estimation of the tree number. Another result that can be obtained from this study is that the original bands of digital aerial image is more capable than the bands obtained by the combination of the original bands in estimating the forest stand parameter. Textural features derived from the infrared band exhibited better performance for DBH, mean height, and tree number, and textural features derived from the red band exhibited better performance for the stand volume and the basal area. For

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the operational use of the method in forest management planning, further studies are required to improve the estimation accuracy. Furthermore, future studies should be conducted in pure and complex forest stands in different ecological regions to better understand the potential digital aerial photos.

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