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Estimation of forest development stage and crown closure using different classification methods and satellite images: A case study from Turkey

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Abstract: The objective of this study is to estimate stand development stages (SDS) and stand crown closures (SCC) of forest using different classification methods (maximum likelihood, support vector machine: linear, polynomial, radial and sigmoid kernel functions and artificial neural network) based on satellite imagery of different resolution (Landsat 7 ETM+ and IKONOS). The results showed that SDS and SCC were estimated with Landsat 7 ETM+ image using the artificial neural network with a 0.83 and 0.78 kappa statistic value, and 92.57 and 89.77% overall accuracy assessments, respectively. On the other hand, SDS and SCC were predicted with IKONOS image using support vector machine (polynomial) method with a 0.94 and 0.88 kappa statistic value, and 95.95 and 91.17% overall accuracy assessments, respectively. Our results demonstrated that IKONOS satellite image and support vector machine (polynomial) method produced a better estimation of SDS and SCC as compared to Landsat 7 ETM+ and other supervised classification methods used in this study.

Keywords: supervised classification; stand attributes; support vector machine; artificial neural network; Landsat 7 ETM+; IKONOS

Forest ecosystems provide goods and services such as timber and non-timber products, soil protection, water production, carbon sequestration, biodiversity conservation, recreation, and aesthetics. The quantity and quality of all these forest ecosystem values are generally linked to forest ecosystem structure including forest stand type, stand age class, growing stock and increment, stand basal area, stand crown closures (SCC), stand development stages (SDS) and tree density. Determination of these forest ecosystem characteristics is named as forest inventory and is very important for sustainable management of forest resources. Especially, SDS and SCC are essential to determine the stand types (Anonymous 2008). Also, each one of them is the major parameter for forest management plans (Sivrikaya et al. 2006; Kadıoğulları, Başkent 2008; Günlü 2012).

Forest inventory studies are based on field measurements and remote sensing methods. Field measurements are mostly expensive, cumbersome and time-consuming (Hyyppa et al. 2000). However, remote sensing methods have been used to estimate and monitor forest stand parameters with reasonable accuracy levels in large areas. Remote sensing technologies have been successfully used in carrying out of forest inventories and have played a vital role in the estimation of forest stand parameters at a low cost and plausible effort with adequate accuracy (Lu et al. 2004). Data obtained by remote sensing can be modified easily and used for estimating and mapping spatial features of forest resources (Pilger et al. 2002).

In this context, different remote sensing data (satellite images) and image classification methods have been used in the estimation of forest stand

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parameters. For example, some studies to predict land use type has been accomplished using Landsat (Lu et al. 2004; Hall et al. 2006; Mohammadi et al. 2010), ASTER (Gebreslasie et al. 2010), IKONOS (Kayitakire et al. 2006; Peuhkurinen et al. 2008), Rapideye (Ustuner et al. 2015). Also different image classification methods such as maximum likelihood (Srivastava et al. 2012; Taati et al. 2015; Topaloğlu et al. 2016), artificial neural network (Srivastava et al. 2012; Hazini, Hashim 2015; Were et al. 2015) and support vector machine (Kavzoglu, Colkesen 2009; Srivastava et al. 2012; Hazini, Hashim 2015; Taati et al. 2015; Ustuner et al. 2015; Were et al. 2015; Topaloğlu et al. 2016) have been used. However, almost all of the studies seek to estimate or monitor land use and land cover including forest ecosystem (Kavzoglu, Colkesen 2009; Srivastava et al. 2012; Hazini, Hashim 2015; Taati et al. 2015; Ustuner et al. 2015; Topaloğlu et al. 2016; Tolessa et al. 2017). In this context, studies focused on estimating forest stand parameters such as SDS and SCC of forests are needed.

The objective of this study is: (*i*) to determine maps of SCC and SDS, (*ii*) to compare image classification algorithms, (*iii*) to compare the performance of satellite images with different spatial resolution. The hypothesis of this research is that high resolution remotely sensed data (IKONOS) would be able to achieve high success with advanced classification algorithms (support vector machines and artificial neural networks) for estimating some stand parameters (SDS and SCC).

MATERIAL AND METHODS

Study area. This study was conducted in Uğurlu Forest Planning Unit, northeastern corner of Turkey (Fig. 1). It is bounded by 42°19'56''E–42°31'02''E and 40°48'40''N–41°01'27''N (ED 1950, UTM zone 38N). The study area is 19,261.6 and 7,573 ha (39.3%) of it is covered by trees that include Scots pine (*Pinus sylvestris* Linnaeus) and Poplar (*Populus tremula* Linnaeus). The elevation varies between 2,048 and 2,785 m with an average slope of 22% (Anonymous 2007).

Data sampling. In this study, 639 temporary sample plots were established systematically with 300 × 300 m intervals in 2005 and DBH, age and height were taken in each sample plot. The coordinates of each sample area were determined by using global positioning system device Garmin eTrex (Garmin, Taiwan). The sizes of the sample plot ranged from 400 to 800 m^2, depending on SCC. The SCC was classified for each sample plot, according to divided four SCC classes such as degraded forest (0–10% closure, no sampling), low coverage (11 to 40%), medium coverage (41–70%) and full coverage (71–100%). DBH was measured in all trees with a diameter bigger than 7.9 cm at breast height. Then, SDS were determined according to measured diam-

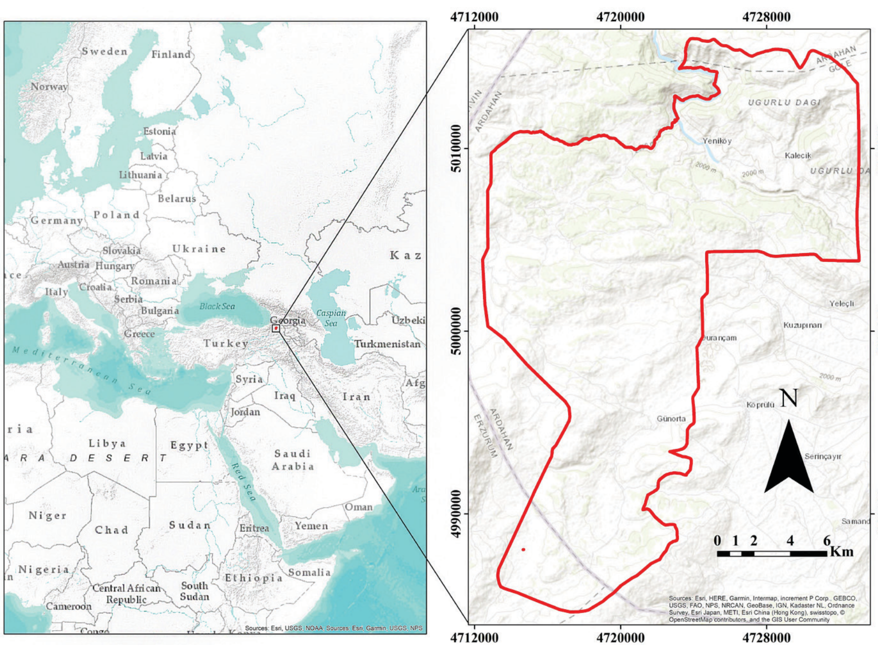

Fig. 1. Location of the study area

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Table 1. Classes of stand crown closures (SCC) and stand development stages (SDS) for satellite images

Landsat 7 ETM+		IKONOS		SCC criteria – crown cover (%)	SDS criteria – average DBH (cm)
SCC	SDS	SCC	SDS		
0	a	0	a	0–10	< 8
1	bc	1	bc	11–40	8–35.9
2	c	2	c	41–70	20–35.9
3	cd	3	cd	> 71	> 20
Other	d	other	d	deforested	> 36
	other	cloud	other	cloudy area	deforested
			cloud		cloudy area

0 – degrade, 1 – low, 2 – medium, 3 – full, a – regenerated, bc – young–mature, c – mature, cd – mature–overmature, d – overmature

eter values, and the categories are: These are regeneration (mean stand diameter < 8 cm), immature (mean stand diameter 8–19.9 cm), mature (mean stand diameter 20–35.9 cm) and over mature (mean stand diameter > 36 cm) (Anonymous 2008). As a result of this process, a ground data map containing tree species, SDS and SCC was obtained.

Satellite images and processing. A Landsat 7 ETM+ scene from 18th of August, 2005 and an IKONOS product from on the 13th of August, 2005 were obtained from the United States Geological Survey Earth Explorer data portal (https://earthexplorer.usgs.gov/, consulted July 5, 2016) and from the General Directorate of Forestry, respectively. Landsat 7 ETM+ satellite image has 30 m spatial resolution and six spectral bands such as visible (ETM 1, ETM, 2, ETM 3), NIR (ETM 4) and MIR (ETM 5 and ETM 7). The IKONOS has four bands red, green and blue with a spatial resolution of 4 m and near infrared with a spatial resolution of 1 m. The pan-sharpened IKONOS satellite image with 1 m resolution was used in this study. The satellite images were orthorectified and georeferenced to UTM Zone 38 projection based on the European Datum 50 using first-order nearest neighborhood rules. Accuracy was checked with 1:25,000 scaled topographical maps and GPS data obtained from the field, both of which proved the accuracy of the rectification. A total of 20 ground points were used to register the Landsat 7 ETM+ and IKONOS images with a rectification error less than 1 pixel image. Atmospheric corrections of these images were also made. Data processing, interpreting, and analysis were performed using ERDAS IMAGINE software (ERDAS LLC 2002).

Image classification. We used Landsat 7 ETM+ and IKONOS satellite images for supervised classification. In addition, we utilized to 5, 4, 3 bands combination for Landsat 7 ETM+, and 4, 3, 2 bands combination for IKONOS in image classification. Since the wavelengths of the infrared boots are longer, it is easier to differentiate the plant species during image classification. In addition, it allows identification of plant species in the shade. As a result, classification success increases (Günlü et al. 2008). Ground reference data was collected as signatures for satellite images and the training points were equally scattered to each SCC and SDS classes with 10 points per class. The signatures were taken from forest cover type map of 2005. SCC (0, 1, 2, 3 and other areas) and SDS (a, bc, c, cd, d, and other areas) classes were classified. Since the IKONOS satellite image used in the study has cloudy areas, the cloud class has been added for the IKONOS satellite image (Table 1).

Maximum likelihood classifier – MLC (Sivrikaya et al. 2006; Günlü et al. 2008), support vector machine (SVM) including linear, polynomial, radial and sigmoid kernel functions (Srivastava et al. 2012; Taati et al. 2015) and artificial neural network – ANN (Bakırman 2014; Hazini, Hashim 2015) classification algorithms were employed as classifier for supervised classification analyses with ENVI software (Version 5.2, 2014). The MLC method was more advantageous in terms of ease of use. The SVM and ANN methods were more complex and so classification processes should be repeated to obtain the most accurate results. Optimal classification parameters of SVM kernel functions and ANN methods were found by checking kappa statistic and overall accuracy at last step of each classification processes, and that was performed in ten times. In the comparison of the success levels of the methods (MLC, SVM, and ANN), kappa sta-

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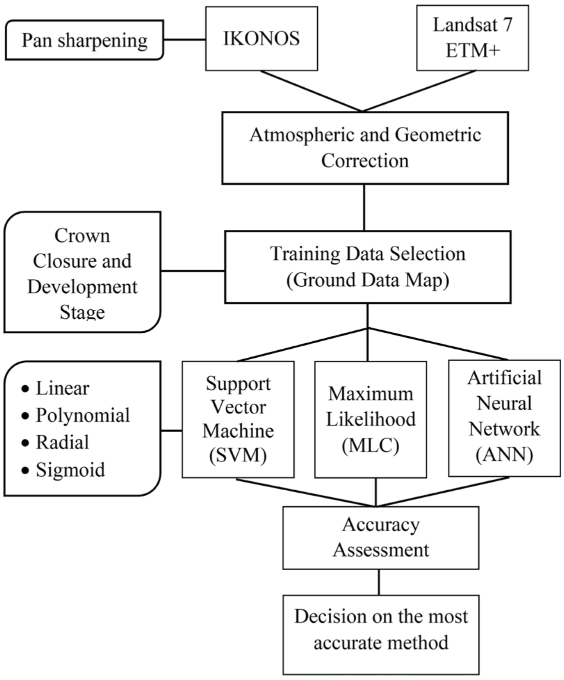

Fig. 2. Flow diagram of the image classification

tistics and overall accuracy values were taken into consideration (Fig. 2).

Classification parameters for support vector machine and artificial neural network. Classification parameters for SVM were degree (1–6), bias (0–7), gamma (> 0.01) and penalty parameter (0–1,000). The degree was used in the polynomial function and it specified to the degree of the polynomial kernel function. Bias was used for polynomial and sigmoid kernel functions. Gamma in kernel functions was used in the polynomial, radial, and sigmoid functions. Penalty parameter specified the degree of misclassification and especially important for non-separable training sets. It was used all kernel functions of SVM. Parameters in ANN were threshold (0–1), rate (0–1), momentum (0–1) and iteration (> 0). Threshold was used to adjust the changes to internal weights. Rate was used to determine the size of weight adjustment. Momentum was encouraged weight changes along the current direction. Iteration specified the number of training repetition (Wu et al. 2004; Chang, Lin 2011; Hsu et al. 2016).

RESULTS

In this study, different satellite image and image classification algorithms were used in predicting SDS and SCC. Optimal parameters for SVM classifiers such as degree, bias, gamma, and penalty parameter and for ANN classifiers such as threshold, rate, momentum, and iteration were obtained by trying to classification. The most appropriate values obtained from these parameters were presented for SVM and ANN methods in Table 2.

The best accuracy values acquired from all methods were given in Table 3. According to the overall accuracy and kappa coefficient, the most accurate

Table 2. Optimal parameters for the most accurate methods

	Value range	SDS	SCC
SVM polynomial using IKONOS			
Degree	1–6	5	5
Bias	0–7	1	1
Gamma	> 0.01	0.125	0.150
Penalty parameter	0–1,000	150	150
ANN using Landsat 7 ETM+			
Threshold	0–1	0.9	0.2
Rate	0–1	0.2	0.2
Momentum	0–1	0.5	0.9
Iteration	> 0	500	500

SVM – support vector machine, ANN – artificial neural network, SDS – stand development stages, SCC – stand crown closures

Table 3. Classification accuracies for MLC, SVM, and ANN

Method	Satellite image			
	Landsat 7 ETM+		IKONOS	
	overall accuracy (%)	kappa	overall accuracy (%)	kappa
Stand development stages				
MLC	86.88	0.73	93.24	0.90
ANN	92.57	0.83	93.87	0.91
SVM linear	91.40	0.80	95.71	0.94
SVM polynomial	91.95	0.82	95.95	0.94
SVM radial	91.69	0.81	95.71	0.94
SVM sigmoid	90.72	0.78	90.88	0.87
Stand crown closures				
MLC	68.54	0.53	88.79	0.85
ANN	89.77	0.78	89.65	0.85
SVM linear	89.49	0.78	90.53	0.87
SVM polynomial	89.60	0.78	91.17	0.88
SVM radial	89.61	0.78	90.87	0.87
SVM sigmoid	88.62	0.75	85.94	0.80

MLC – maximum likelihood classifier, ANN – artificial neural network, SVM – support vector machine

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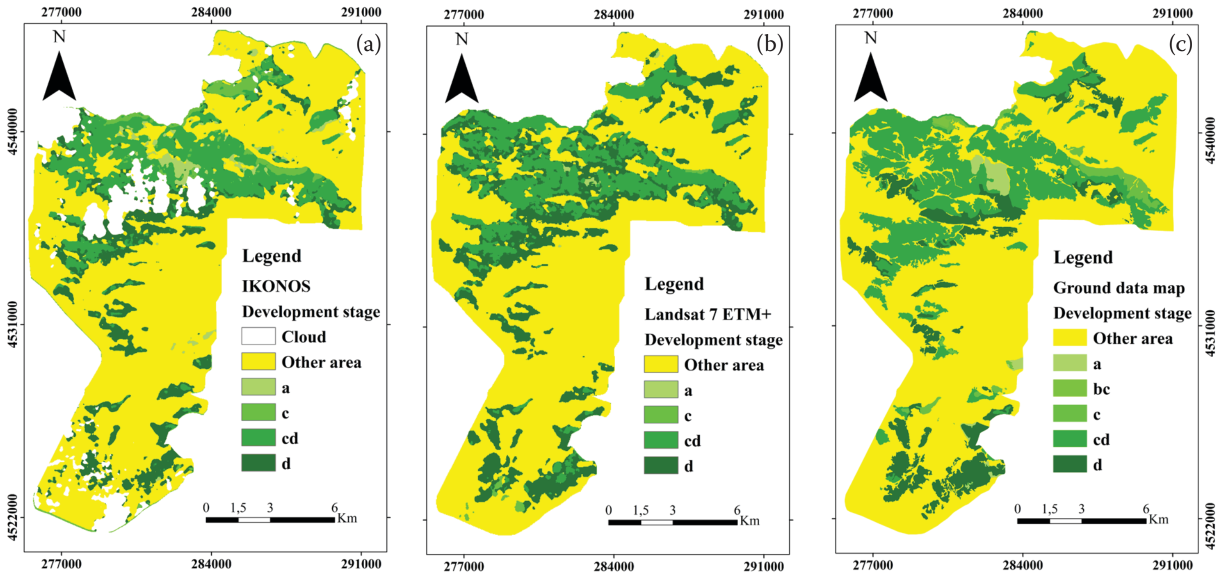

Fig. 3. Visual comparison of resulting maps for stand development stages by the most accurate methods: support vector machine polynomial for IKONOS (kappa = 0.94) (a), artificial neural network for Landsat 7 ETM+ (kappa = 0.83) (b), ground data maps (c)

a – regenerated, bc – young–mature, c – mature, cd – mature–overmature, d – overmature

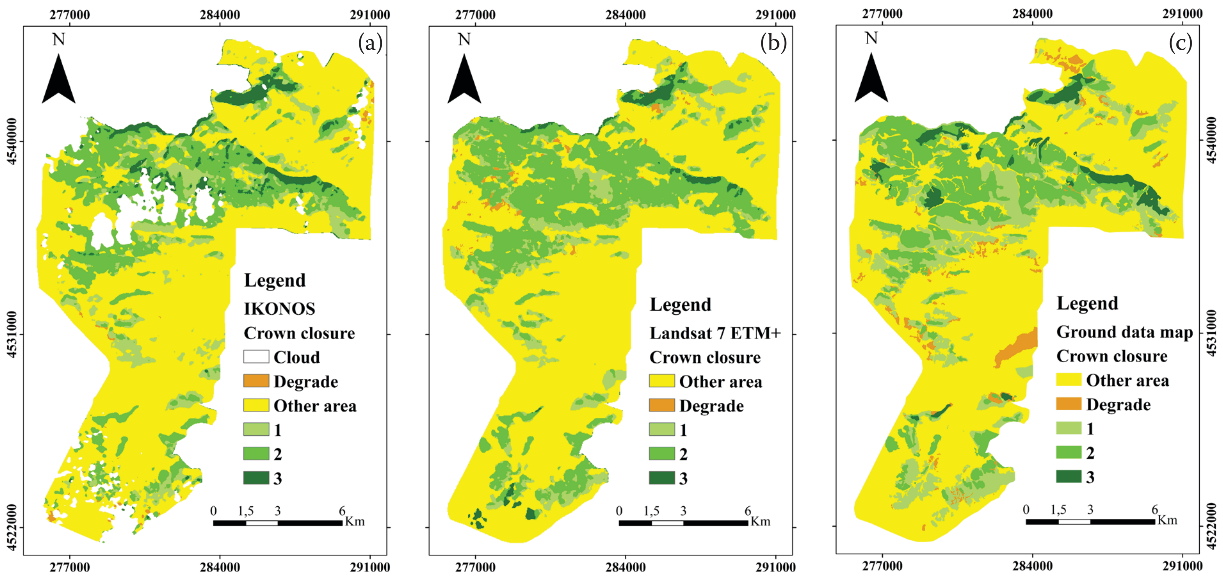

Fig. 4. Visual comparison of resulting maps for stand crown closures by the most accurate methods: support vector machine polynomial for IKONOS (kappa = 0.88) (a), artificial neural network for Landsat 7 ETM+ (kappa = 0.78) (b), ground data maps (c)

1 – low, 2 – medium, 3 – full

methods were selected and focused them. One of the selected methods is ANN classifiers with Landsat 7 ETM+ satellite image, and the other method is SVM polynomial function with IKONOS satellite image for SCC and SDS. Kappa coefficient was 0.83 with Landsat 7 ETM+ based on ANN and 0.94 with IKONOS based on SVM polynomial function for SDS. Kappa coefficient was 0.78 with Landsat 7 ETM+ based on ANN and 0.88 with IKONOS based on SVM polynomial function for SCC (Table 3).

Classification map from IKONOS satellite image had better classification pattern in terms of “a” and “c” SDS compare to Landsat 7 ETM+ (Fig. 3). Degraded areas could not be classified sufficiently for

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both satellite images. However, IKONOS had better in terms of "3" SCC classes (Fig. 4). Containing cloud on IKONOS satellite image was a disadvantage for interpreting classification map.

In addition, confusion matrixes based on pixel were generated for all image classifications and presented for the most accurate classification methods in Table 4. Satellite images and methods used in classifications were insufficient for classification of "bc" SDS with 26.84 ha (Table 4). "Degrade" SCC class was classified as "1" and "other areas" (Table 4). Accuracy assessments for the same methods were illustrated in Table 5. According to producer accuracy, "a" and "other" classes were the best clas-

Table 4. Confusion matrix for stand development stages and stand crown closures

Stand development stages									Stand crown closures							
Class	ground truth (pixel)								class	ground truth (pixel)						
	a	bc	c	cd	d	other	cloud	total		1	2	3	degrade	other	cloud	total
Support vector machine polynomial classifiers for IKONOS																
a	646							646	1	1,429			74	17		1,520
bc								0	2	3	1,224	103				1,330
c		152	252	19				423	3		23	806			31	860
cd		46	273	971	30			1,320	degrade				7			7
d	10		4		1,033	6		1,053	other	319			752	5,975		7,046
Other			3		12	5,986		6,001	cloud		1				4,225	4,226
Cloud							4,256	4,256	total	1,751	1,248	909	833	5,992	4,256	14,989
Total	656	198	532	990	1,075	5,992	4,256	13,699								
Artificial neural network classifiers for Landsat 7 ETM+																
a	106							106	1	2,029	19		203	241		2,492
bc								0	2	158	2,942	305	1			3,406
c			78					78	3		2	583				585
cd	2	136	176	2,706	125			3,145	degrade	9			52			61
d	315	28	39	247	1,955	170		2,754	other	603	2		972	16,470		18,047
Other	293		20		165	16,541		17,019	total	2,799	2,965	888	1,228	16,711		24,591
Total	716	164	313	2,953	2,245	16,711		23,102								

a – regenerated, bc – young–mature, c – mature, cd – mature–overmature, d – overmature, 1 – low, 2 – medium, 3 – full

Table 5. Accuracy assessment for stand development stages and stand crown closures

Stand development stages					Stand crown closures				
Class	accuracy (%)		accuracy (pixel)		class	accuracy (%)		accuracy (pixel)	
	producer	user	producer	user		producer	user	producer	user
Support vector machine polynomial classifiers for IKONOS									
a	98.48	100.00	646/656	646/646	1	81.61	94.01	1,429/1,751	1,429/1,520
bc	0.00	0.00	0/198	0/0	2	98.08	92.03	1,224/1,248	1,224/1,330
c	47.37	59.57	252/532	252/423	3	88.67	93.72	806/909	806/860
cd	98.08	73.56	971/990	971/1,320	degrade	0.84	100.00	7/833	7/7
d	96.09	98.10	1,033/1,075	1,033/1,053	other	99.72	84.80	5,975/5,992	5,975/7,046
Other	99.90	99.75	5,986/5,992	5,986/6,001	cloud	99.27	99.98	4,225/4,256	4,225/4,226
Cloud	100.00	100.00	4,256/4,256	4,256/4,256					
Artificial neural network classifiers for Landsat 7 ETM+									
a	14.80	100.00	106/716	106/106	1	73.95	80.92	2,070/2,799	2,070/2,558
bc	0.00	0.00	0/164	0/0	2	98.38	87.49	2,917/2,965	2,917/3,334
c	24.92	100.00	78/313	78/78	3	65.99	98.65	586/888	586/594
cd	91.64	86.04	2,706/2,953	2,706/3,145	degrade	0.08	100.00	1/1,228	1/1
d	87.08	70.99	1,955/2,245	1,955/2,754	other	98.49	90.91	16,459/16,711	16,459/18,104
Other	98.98	97.19	16,541/16,711	16,541/17,019					

a – regenerated, bc – young–mature, c – mature, cd – mature–overmature, d – overmature, 1 – low, 2 – medium, 3 – full

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sified for SDS with IKONOS satellite image and, "a" and "c" classes were the best for user accuracy results with Landsat 7 ETM+ satellite image (Table 5). In SCC classification, "2" and "other" classes were the best for producer accuracy results with IKONOS satellite image and, "3" and "degrade" classes were the best for user accuracy results with Landsat 7 ETM+ satellite image (Table 5).

DISCUSSION

Different satellite images (IKONOS and Landsat 7 ETM+) and image classification algorithms (MLC, SVM, and ANN) were used for investigating the SCC and SDS. The best accuracy results showed that SDS and SCC were predicted with IKONOS image using SVM polynomial kernel function with a 0.94 and 0.88 kappa statistic values, and 95.95 and 91.17% overall accuracy assessments, respectively. The other results indicated that SDS and SCC were estimated with Landsat 7 ETM+ image using ANN with a 0.83 and 0.78 kappa statistic values, and 92.57 and 89.77% overall accuracy assessments, respectively.

There are many studies about satellite image classification for stand parameters using MLC (Sivrikaya et al. 2006; Başkent, Kadıoğulları 2007; Günlü et al. 2008; Kadıoğulları, Başkent 2008; Sivrikaya 2011; Günlü 2012). However, there are a few studies about different classification methods such as SVM and ANN to classify SDS and SCC in the literature (Bulut et al. 2017). Sivrikaya et al. (2006) classified land cover classes in Artvin Forest Planning Unit with 82.1% accuracy and 0.79 kappa statistic. Başkent and Kadıoğulları (2007) classified land use and forest cover types in İnegöl Forest Enterprise which has typical alluvial areas with a higher overall classification accuracy of 91.04% and 0.90 kappa statistics value. Regarding MLC classification method, Günlü et al. (2008) classified SDS, SCC and stand type using Landsat 7 ETM+ with 0.89, 0.86 and 0.76 kappa statistic, respectively. Kadıoğulları and Başkent (2008) classified land use and forest cover types in Gümüşhane Forest Enterprise which has a typical mountain area, with an accuracy of 86.58% and 0.8452 kappa statistic. Sivrikaya (2011) used Landsat 7 ETM+ and classified SDS, SCC and forest cover type. Kappa statistics were obtained 0.90, 0.92 and 0.67 for SDS, SCC and forest cover type, respectively. Günlü (2012) found that 0.83, 0.88 and 0.92 kappa statistics for SDS, SCC and land use classification using Landsat TM.

When the literature was examined, there were also many studies about different classification methods. Srivastava et al. (2012) examined the land use classification generated from Landsat TM satellite image using MLC, SVM linear, SVM polynomial, SVM radial, SVM sigmoid, and ANN methods and they found that the kappa statistic values were 0.7171, 0.7496, 0.7488, 0.7493, 0.7482 and 0.7499, respectively. Bakırman (2014) reported that the accuracy of land use classifications were 91.06, 92.34 and 90.64% for MLC, SVM linear and ANN methods, respectively. In another study, Taati et al. (2015) classified land use classes using Landsat 5 TM with MLC and SVM classification methods, and kappa statistic values were found 0.72 and 0.82, respectively. Hazini and Hashim (2015) classified land use using SVM and ANN methods with an ASTER satellite image and found 0.94 of kappa value of SVM and 0.82 of kappa value of ANN. Kulkarni and Lowe (2016) found that kappa statistics of land use classification were 0.90, 0.99 and 0.98 using Landsat 8 with MLC, SVM and ANN classification methods, respectively. Bulut and Günlü (2016) used MLC and SVM linear, polynomial, radial, sigmoid kernel functions and classified land use with Landsat 8. Kappa statistics obtained with these methods were 0.81, 0.77, 0.79, 0.75 and 0.63, respectively. Bulut et al. (2017) used Landsat TM satellite image with MLC and SVM kernel functions for classification of SCC. Kappa statistics were 0.60 for MLC and 0.68 for SVM radial and polynomial kernel functions.

Our results were not consistent with the study of Günlü et al. (2008), Sivrikaya (2011) and Günlü (2012). Our study demonstrated that kappa statistics values were found 0.73 and 0.53 for SDS and SCC using Landsat 7 ETM+ with MLC method. However, we achieved a significant improvement with 0.94 kappa statistic for the development stage by using IKONOS satellite image and SVM linear, polynomial and radial kernel functions. The use of high-resolution satellite image and advanced classification technique increased the success rate.

CONCLUSIONS

The result of this study shows that SDS and SCC were estimated with Landsat 7 ETM+ image

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using ANN with a 0.83 and 0.78 kappa statistic value, and 92.57 and 89.77% overall accuracy assessments, respectively. The other result indicated that SDS and SCC were predicted with IKONOS image using SVM polynomial kernel function with a 0.94 and 0.88 kappa statistic value, and 95.95 and 91.17% overall accuracy assessments, respectively. The highest success was achieved for the SDS using IKONOS with SVM polynomial kernel function. IKONOS with SVM and Landsat 7 ETM+ with ANN gave better results. SVM classification method had better performance with the high spatial resolution satellite image. In the direction of our hypothesis, high resolution remotely sensed data with advanced classification algorithms gave higher success. There are many studies about the classification of stand parameters using MLC in Turkey. However, there is a need for the use of different classification methods such as SVM and ANN in order to forest stand; therefore, we think this study represents a contribution to the forestry community.

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