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## **Oral presentation**

# Evaluation of different supervised classification algorithms for crown closure classes: A case study of Yapraklı Forest Planning Unit, Çankırı

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**Abstract:** Remote sensing and Geographic Information Systems (GIS) provide novel occasions for forest inventory and ecosystem values. Forest inventory has been made by field measurements and remote sensing methods. Field measurements are mostly expensive, cumbersome and time-consuming. Recently, satellite images have been used successfully for large area applications, such as for national forest inventories. The use of satellite images has played significant role in determining forest stand attributes such as crown closures, development stages and land use. 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 estimation of forest stand parameters at a low cost and plausible effort with adequate accuracy. There are many algorithms that can be used to classify satellite images. Support vector machines (SVM), highest probability, maximum likelihood (MLC), closest distance, classifier of Mahalanobis, artificial neural networks and decision trees are some of them. The objective of this research was to classify crown closure classes using Landsat TM satellite image with different supervised classification algorithms in Yaprakli Forest Planning Unit. For this purpose, the MLC method and linear, polynomial, radial and sigmoid kernel functions for SVM were used. The SVM method 80002 kappa statistic and 72% overall accuracy assessments, respectively. The SVM radial function for these values was 0.6797 and 80%.

Keywords: Crown closure, Image classification, Landsat TM, Maximum likelihood classification, Support vector machine

#### 1. Introduction

Remote sensing are being investigated in almost every aspect and are being continuously improved especially in the field of forestry. One of the remote sensing techniques researched and developed in forestry is satellite image classification. Some of these techniques such as maximum likelihood, support vector machines, neural network, decision trees are widely used to different criteria such as development stage, crown closure, tree species, land use. Moreover, new techniques are always being investigated for image classification and evaluated for maximum accuracy and ease of use (Günlü et al., 2008; Kavzoğlu and Çölkesen, 2010; Otukei and Blasche, 2010; Günlü et al., 2011; Srivastava et al., 2012; Günlü, 2012; Taati et al., 2014; Bulut and Günlü, 2016). We focused on estimating crown closure with remote sensing techniques.

Crown closure is an indicator for productivity of forests. Especially, it is an effective parameter to decide on silvicultural applications. Remote sensing studies are used effectively in estimating this parameter. In this study, we compared performance of image classification techniques (maximum likelihood, SVM linear, SVM polynomial, SVM radial and SVM sigmoid kernel functions) in terms of crown closure.

### 2. Material and method

### 2.1. Study area

Our study area, Yapraklı Forest Planning Unit is located in Ankara Regional Forest Directorate with a total area of 29380.30 ha (Figure 1). It is bounded by 563243-572062 on the east longitudes and 4501061-4522167 on the North latitudes (ED 1950, UTM Zone 36N). Average altitude, precipitation and temperature of study area are 1348 m, 397.7 mm and 11.1 C°, respectively. The study area is covered by trees that include Black pine, Scots pine, Fir, Cedar, Oak and Poplar (Table 1).

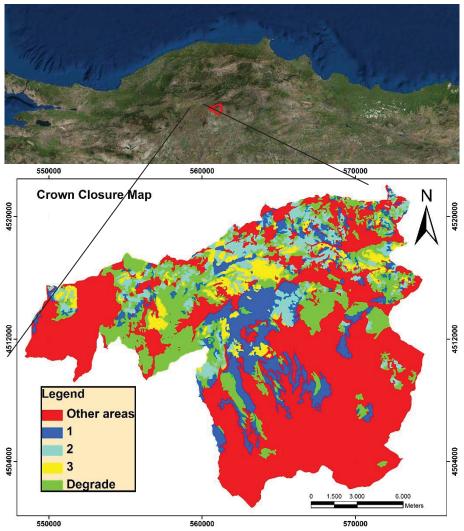


Figure 1. Study area

## 2.2. Satellite image and classification

The Landsat TM satellite image, which was consisted of six spectral bands (TM1, TM2, TM3, TM4, TM5 and TM7) with 30 m spatial resolution, was acquired on 2010. Stand map of Yapraklı Forest Planning Unit was used as reference data. Supervised classification methods that maximum likelihood, SVM linear, SVM polynomial, SVM radial and SVM sigmoid were applicated with ENVI 5.2 software. Five different crown closure classes were created. These classes are 1 (%11-40), 2 (%41-70), 3 (%71-100), degrade (%0-10) and other areas (settlement, agriculture). Signatures for each classes were taken through stand map and five different supervised classification methods were tested for crown closure. The most accurate parameters for SVM methods were found through trial and error (Table 1).

Table 1. SVM classification parameters	Table 1	. SVM	classification	parameters
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	aton parameters				
Methods	р	g	r	d	
SVM Linear	200				
SVM Radial	1000	0.150			
SVM Polynomial	1000	0.150	1	6	
SVM Sigmoid	100	0.150	1		
-					

p: penalty parameter, g: gamma, r: bias and d: degree of kernel polynomial

#### 3. Results and discussion

The most accurate classification was applicated with SVM radial method. It's kappa statistics value was 0.6797 and overall accuracy was 79.6704 %. The lowest result was obtained for SVM sigmoid method. Kappa statistics and overall accuracy of this method were 0.5577 and 72.3290%, respectively. Performance criteria and confusion matrix of all methods were represented (Table 2-7).

Classification metho		Kappa statistics				ccuracy (%)	
Maximum likelihoo	d	0.6002			72.1903		
SVM linear		0.5933			74.4955		
SVM polynomial		0.6792			79.6241		
SVM radial		0.6797			79.6704		
SVM sigmoid		0.5577			72.3290		
Table 3 Confusion	n matrix of maximum	likelihood method					
Class	Other areas	Degrade	1	2	3	PA (%)	UA (%)
Other areas	4500	71	94	8	2	76.40	96.26
Degrade	435	1162	94	74	9	63.22	65.50
1	896	353	809	114	18	63.95	36.94
2	59	243	229	572	92	61.31	47.87
3	0	9	39	165	755	86.19	78.00
	n matrix of SVM linea						
Class	Other areas	Degrade	1	2	3	PA (%)	UA (%)
Other areas	5454	540	325	36	2	92.60	85.80
Degrade	313	961	382	173	25	52.29	51.83
1	118	212	425	105	29	33.60	47.81
2	5	114	122	495	108	53.05	58.65
3	0	11	11	124	712	81.28	82.98
3 Table 5. Confusion	n matrix of SVM poly	nomial method					
3 Table 5. Confusion Class	n matrix of SVM poly Other areas	nomial method Degrade	1	2	3	PA (%)	UA (%)
3 Cable 5. Confusion Class Other areas	n matrix of SVM poly Other areas 5475	nomial method Degrade 339	1 318	2 22	32	PA (%) 92.95	UA (%) 88.94
3 Cable 5. Confusion Class Other areas Degrade	n matrix of SVM poly Other areas 5475 269	nomial method Degrade 339 1191	1 318 163	2 22 140	3 2 8	PA (%) 92.95 64.80	UA (%) 88.94 67.25
3 Table 5. Confusion Class Other areas Degrade 1	n matrix of SVM poly Other areas 5475 269 144	nomial method Degrade 339 1191 234	1 318 163 685	2 22 140 163	3 2 8 46	PA (%) 92.95 64.80 54.15	UA (%) 88.94 67.25 53.85
3 Sable 5. Confusion Class Other areas Degrade 1 2	n matrix of SVM poly Other areas 5475 269 144 2	nomial method Degrade 339 1191 234 73	1 318 163 685 92	2 22 140 163 548	3 2 8 46 118	PA (%) 92.95 64.80 54.15 58.74	UA (%) 88.94 67.25 53.85 65.79
3 Cable 5. Confusion Class Other areas Degrade 1	n matrix of SVM poly Other areas 5475 269 144	nomial method Degrade 339 1191 234	1 318 163 685	2 22 140 163	3 2 8 46	PA (%) 92.95 64.80 54.15	UA (%) 88.94 67.25 53.85
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3 Table 5. Confusion Class Other areas Degrade 1 2 3 Table 6. Confusion Class Other areas Degrade 1 2 3 Table 7. Confusion Class Other areas Degrade 1 2 3 Class Other areas Degrade Class Other areas Degrade Class Other areas Degrade Class Other areas Degrade Other areas Degrade Class Other areas Degrade Other areas Other areas Degrade Other areas Degrade Other areas Other areas Other areas Other areas Other areas Other areas Other areas Other areas Other areas	n matrix of SVM poly Other areas 5475 269 144 2 0 n matrix of SVM radia Other areas 5505 241 142 2 0 n matrix of SVM sigm Other areas 5416	nomial method Degrade 339 1191 234 73 1 al method Degrade 337 1162 257 81 1 noid method Degrade 643	1 318 163 685 92 7 1 309 158 695 97 6 1 285	$     \begin{array}{r}       2 \\       22 \\       140 \\       163 \\       548 \\       60 \\       \hline       2 \\       24 \\       130 \\       161 \\       553 \\       65 \\       \hline       2 \\       46 \\       \end{array} $	3 2 8 46 118 702 3 1 8 48 128 691 3 1	PA (%) 92.95 64.80 54.15 58.74 80.14 PA (%) 93.46 63.22 54.94 59.27 78.88 PA (%) 91.95	UA (%) 88.94 67.25 53.85 65.79 91.17 UA (%) 89.14 68.39 53.34 64.23 90.56 UA (%) 84.74
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Table 2. Performance of supervised classification methods

All classification methods have generally low accuracy for classification of degrade, 1 and 2 crown closure classes. The reason for this, reflectance values of these classes were close to each other in training areas. So, classification methods were not distinguished correctly. The highest accuracy rate was obtained for other areas and 3 crown closure classes. The most accurate methods in terms of producer accuracy were SVM radial (other areas), SVM polynomial (degrade) and maximum likelihood (1,2 and 3 crown closure). The most accurate methods in terms of user accuracy were maximum likelihood (other areas), SVM radial (degrade) and SVM polynomial (1, 2 and 3 crown closure). In addition that all classification maps were displayed (Figure 2).

48.87

80.02

53.58

81.42

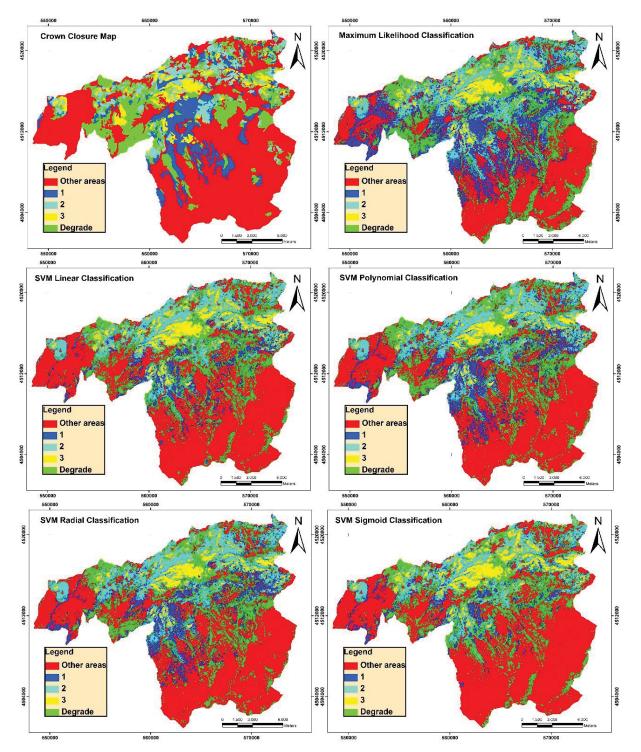


Figure 2. Stand and classification maps

#### 4. Conclusions

In this study, maximum likelihood, SVM linear, SVM polynomial, SVM radial and SVM sigmoid supervised classification methods were compared in terms of crown closure. Landsat TM satellite image was used for classification. Although the most accurate method was SVM radial according to accuracy rate, maximum likelihood, which is the most common classification method, is more suitable for ease of use. In conclusion, it should be applied to different satellite images, fields and parameters so that better comparison of methods can be made.

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