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Forest canopy density assessment using different approaches – Review

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Abstract

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Crown canopy is a significant regulator of forest, affecting microclimate, soil conditions and having an undeniable role in a forest ecosystem. Among the different materials and approaches that have been used for the estimation of crown canopy, satellite based methods are among the most successful methods regarding cost-saving efforts and different kinds of options for measuring the crown canopy. Different types of satellite sensors can result in different outputs due to their various spectral and spatial resolution, even when using the same methodologies. The aim of this review is to assess different remote sensing methods for forest crown canopy density assessment.

Keywords: satellite sensors; vegetation index; classification methods; pixel based; spectral analyses

Recently, measuring the crown canopy of a forest has been part of the inventory schedule. The tree crown size determines, among others, carbon sequestration, shading, filtering of fine air particulates, risk of wind-breaking and tree growth. The dependence of the crown size on resource supply, species and tree age complicates an accurate evaluation of the space requirement of a tree, its size-dependent functions and services in forested areas. Two important factors that affect measuring the crown canopy are: definition of crown canopy and the technique used to estimate the crown canopy (Korhonen et al. 2006).

There are three different methods for measuring or estimating the crown canopy in a forest: (*i*) ground measurement at the study area (Sarvas 1953; Rautiainen et al. 2005; Korhonen et al. 2006), (*ii*) statistical approaches, if the information such as basal area or DBH and number of stems is available, (*iii*) remote sensing data like aerial photographs (Pitkänen 2001; Culvenor 2003), satellite data (Iverson et al. 1989; Gemmell 1999) or laser scanner data (Næsset et al. 2004). From among these the satellite based models are the most common approach for measuring the crown canopy and they can be divided into two main categories.

Remote sensing methods

In these methods, mainly different kinds of algorithms or enhancement functions are applied to a satellite image in order to resolve more clear bands like: soil, atmosphere or vegetation indicators, texture analysis, tasselled cap transformation, etc. Slicing, image arithmetic (Boles et al. 2004; Matsushita et al. 2007), segmentation and multispectral image classification (Wang 1990; Seong, Usery 2001) are the most common approaches in this category. Although supervised classification is

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the most complete one, there are some disadvantages of this approach. Requirement for training area establishment for estimation is one of those impediments. Training area establishment is time consuming, difficult to fulfil and sometimes it cannot give right or enough information.

Biophysical response modelling

The International Tropical Timber Organization developed a new method to solve the problems of remote sensing methods. The advantage of this approach is that it does not need any training samples during the process of so called forest canopy density (FCD) mapping model known as Rikimaru's approach. The FCD mapping model uses the crown canopy density as an important factor for assessing the crown status.

The main purpose of this paper is to review different approaches to estimation and classification of crown canopy density as well as the possibility of remote sensing methods for providing the needed material.

Description of the individual methods

Main bands and analysed spectral data. Remote sensing has been widely used with varying degrees of success to quantify spatially forest structure characteristics such as crown cover, tree density, tree diameter, basal area, tree height, tree age, biomass, and leaf area index. Nowadays using a wide range of software with different enhancement options makes an opportunity for researchers to detect and clarify their interest variables easier. Image contrast enhancement, linear principle component analysis and tasselled cap transformations and texture analysis are some of the common processing methods for image enhancement in remote sensing software such as PCI Geomatica, ERDAS, IDRISI, etc. Pixel based (the most common approach) (Shao et al. 1996) and object based approaches (Shataee 2003) have been used for the classification of crown canopy in related researches.

The development of robust object based methods suitable for medium to high resolution satellite imagery provides a valid alternative to "traditional" pixel based methods (Baatz et al. 2004; Benz et al. 2004). The object oriented classification involves segmenting an image into objects (groups of pixels). There are two main methods for object based approaches:

(1) Direct method such as (*i*) region growing technique – can be employed to a group of adjacent pixels with similar spectral values into individual objects (Gao et al. 2006), (*ii*) edge detection technique – can be used to identify discontinuities (object boundaries or edges) throughout the image, these boundaries can be used to build polygons for the object based classification (Carleer, Wolff et al. 2006);
(2) Indirect method: here, the imagery is supplemented with another spatial data, often digital vector map data. The objects characterised by the vector polygons are assigned land cover values derived from the imagery.

Also, some researchers (Tucker 1979; Huang et al. 2001) used the main bands of satellites (Landsat 7 ETM+) for the classification of crown canopy.

Moreover, there are different image classification procedures used for different purposes by various researchers (Ernst, Hoffer 1979; Tucker 1979; Butera 1983; Lo, Watson 1998; Liu et al. 2002; Ozesmi, Bauer 2002; Dean, Smith 2003; Pal, Mather 2003).

These techniques are distinguished in two main ways: (*i*) unsupervised classification which requires no training data (Ghazanfari 1996; Shirian 1997; Mirakhorlo 2003; Hosseini et al. 2004), (*ii*) supervised classification including maximum likelihood (Butera 1983; Lee, Park 1992; Yi et al. 1994; Clark et al. 2005), minimum distance to mean (Huguenin et al. 1997), Mahalanobis, Fisher classifier, parallelepiped (Hines et al. 1993) and Bayesian formulation based classification (Schistad-Solberg et al. 1994) (Fig. 1). These algorithms were used by different studies such as Ramtin Nia (1997), Abbasi (2001), and Hosseini et al. (2004). Recently, non-parametric algorithms are widely used for the classification of forest attributes like crown canopy. Some of those data mining classifier algorithms have been commonly used in recent studies such as:

(*i*) *k*-Nearest neighbour (*k*-NN) method is one of the simplest and most popular data-mining algorithms used for classification and regression. *k*-NN is widely used for the estimation of forest description using various topographic and remote-sensing data (Breiman 2001, 2002). In *k*-NN implementations, three factors should be determined including the number of *k*, the type of distance measure and weights for the nearest neighbours;
(*ii*) Support vector machine classification: this algorithm is suitable for both classification and regression techniques based on the statistical

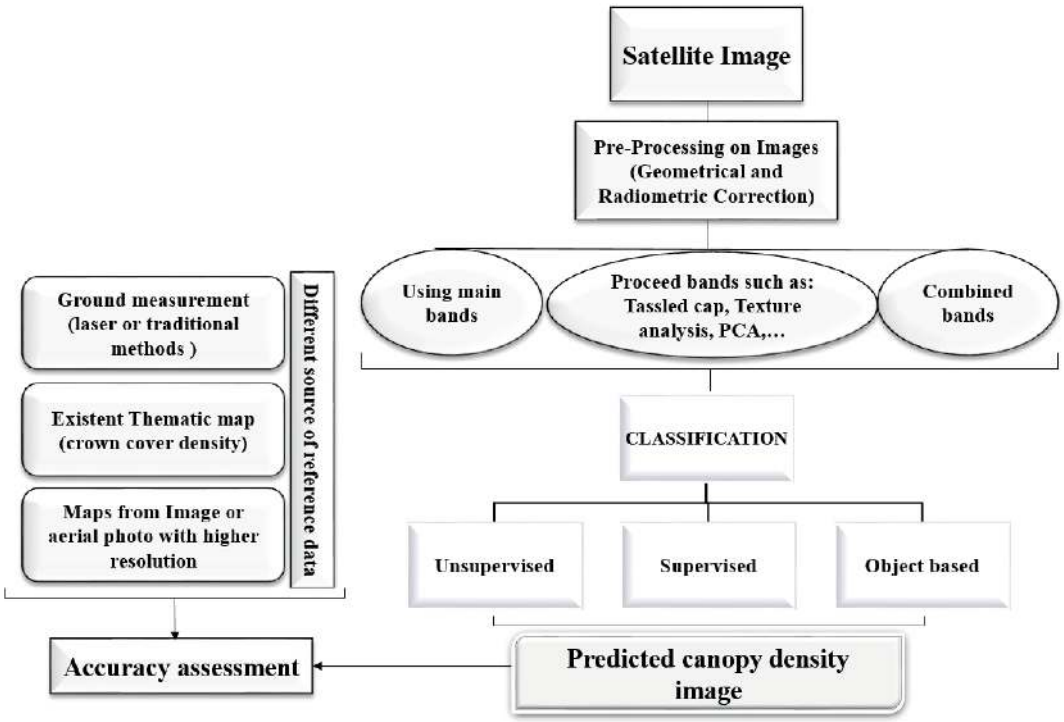

Fig. 1. The main stages of image classification in different methods using different reference data
PCA – principal component analysis

learning theory (Walton 2008). Generally, support vector machine (SVM) focuses on the boundary between classes and maps the input space created by independent variables using a non-linear transformation according to a kernel function. Liner, polynomial radial basis function (RBF) and sigmoid are the most commonly used kernel types. The RBF is the most popular kernel, which is used in SVMs (Cortez, Morais 2007; Durbha et al. 2007). According to our literature review, SVM has been used for forest classification (Zhang, Ma et al. 2008; Ostapowicz et al. 2010). In his work, Sheeren et al. (2016) found out the SVM among various non-parametric techniques to be the best classifier with very close results to other classifiers among them (*k*-NN and random forest);

(*iii*) Random forest (RF) is a new algorithm to the field of data mining, designed to produce accurate predictions that do not overfit the data (Breiman 2002). RF can also be used for regression-type problems (to predict a continuous dependent variable) and classification problems (to predict a categorical dependent variable). Implementation of RF depends on the regularization of decision tree and stopping parameters. The decision tree model parameters include the maximum number of trees that must be grown in the forest and the number of variables (*k* predictor or independent variables in each node for predicting dependent values) that are randomly selected in each node. Alternatively, choosing a small number of predictor variables may downgrade the prediction performance, because this can exclude variables that may account for most of the variability and trends in the data (StatSoft, Inc. 2010). The stopping parameters or control parameters are used to stop running the algorithm when satisfactory results have been achieved (Shataee et al. 2012). In some studies such as Garzón et al. (2008) and Shataee et al. (2012), the RF has been used for the prediction of forest attributes.

Vegetation indicators. Vegetation indicators are based on the spectral reflection of plants (red and near infra-red range). There are three categories for vegetation indicators (Table 1):

(*i*) Mean vegetation indices: almost most of these indicators have been used for measuring the frequency of plants and biological characteristics of crown cover. These indicators just use red and infra-red bands. Normalized difference vegetation index (NDVI) (Rouse et al. 1973), ratio vegetation index (also known as the simple ratio) (Birth, McVey 1968), green normalized difference vegetation index (Buschmann, Nagel 1993) and green difference vegetation index (Sripada et al. 2006) are some of the most common indicators in this category;

Table 1. Categories of vegetation indices

Vegetation index category	Indices	Explanation
Mean	NDVI	(NIR – red)/(NIR + red)
	RVI	NIR/red
	GDVI	NIR – green
	GNDVI	(NIR – green)/(NIR + green)
Atmospherically resilient	GEMI	$\eta \times (1 - 0.25 \times \eta) - [(\text{red} - 0.125)/(1 - \text{red})]$
	GARI	NIR – [green – (blue – red)]/NIR × [green – (blue – red)]
	VIg	(green – red)/(green + red)
	VARIg	(green – red)/(green + red – blue)
Soil-adjusted	SAVI	$[(\text{NIR} - \text{red})/(\text{NIR} + \text{red} + L)] \times (1 + L)$
	MSAVI2	$[2 \times \text{NIR} + 1 - \sqrt{(2 \times \text{NIR} + 1)^2 - 8 \times (\text{NIR} - \text{red})}]/2$
	GSAVI	$[(\text{NIR} - \text{green})/(\text{NIR} + \text{green} + L)] \times (1 + L)$
	TSAVI	$[a \times (\text{NIR} - a \times \text{red} - b)]/[a \times \text{NIR} + \text{red} - (a \times b) + X \times (1 + a^2)]$

NDVI – normalized difference vegetation index, RVI – ratio vegetation index, GDVI – green difference vegetation index, GNDVI – green normalized difference vegetation index, GEMI – global environmental monitoring index, GARI – green atmospherically resilient index, VIg – vegetation index green, VARIg – vegetation atmospherically resilient index green, SAVI – soil-adjusted vegetation index, MSAVI2 – modified soil-adjusted vegetation spectral index, GSAVI – green soil-adjusted vegetation index, TSAVI – transformed soil-adjusted vegetation index, NIR – near infra-red band, $\eta = (2 \times (\text{NIR}^2 - \text{red}^2) + 1.5 \times \text{NIR} + 0.5 \times \text{red})/(\text{NIR} + \text{red} + 0.5)$, $L = 0.5$, a – the slope of the soil line, b – the intercept of the soil line, X – adjustment factor

(*ii*) Atmospherically resilient vegetation indices: these indicators use the blue or green bands besides the red and infra-red bands in order to solve the dependence of vegetation indices on atmospheric effects. Global environmental monitoring index (Pinty, Verstraete 1992), green atmospherically resilient index (Gitelson et al. 2002), vegetation index green (Gitelson et al. 2002), and vegetation atmospherically resilient index green (Gitelson et al. 2002) are some of these indices;

(*iii*) Soil-adjusted vegetation indices: by using one parameter called L these indicators try to decrease the soil effect on NDVI index. The L factor is an adjustment parameter, the amount of this factor for the area with low density 1, for the area with intermediate density 0.5 (the most common amount) and for the area with high crown cover 0 is considered. Soil-adjusted vegetation index (Huete 1988), modified soil-adjusted vegetation spectral index (MSAVI2) as it is described in Eq. 19 in Qi et al. (1994), transformed soil-adjusted vegetation index, the median soil line values of which reported in Baret and Guyot (1991) are $a = 1.2$ and $b = 0.04$, and green soil-adjusted vegetation index (Sripada et al. 2006) are some indicators from this category.

Different studies arrived at different indices as the best vegetation index based on the density of their case study. Sensitivity of indicators to the amount of crown canopy and soil or gap area percentage can cause different results in different studies. For example NDVI and MSAVI2 in the area with lower or without crown canopy density have higher accuracy (Abdi et al. 2009).

Biophysical response modelling (FCD model). FCD is used as an important variable for the characteristics of forest status. FCD is based on the growth component and it can illustrate the degree of degradation (Rikimaru et al. 1999). FCD model shows the growth phenomena of forests, which is quantitative analysis. The degree of forest density is expressed in percentages: i.e. 10, 20, 30, 40% and so on.

Also, this model makes it possible to monitor changes in the forest crown canopy density over time. This method also makes it possible to monitor the transformation of forest conditions over time and it can assess the progress of reforestation activities.

Based on four different indicators, FCD can calculate the percentage of canopy density for each pixel. These indices are: (*i*) advanced vegetation index (AVI), (*ii*) bare soil index (BI), (*iii*) canopy shadow index or scaled shadow index (SSI), (*iv*) thermal index (TI) (Rikimaru et al. 2002; Godinho et al. 2016) (Table 2). The principle of this method is shown in Fig. 2. There are direct and indirect relationships between forest canopy and FCD components (Table 3).

In this method like in other approaches, first of all the geometric accuracy and spectral quality of

Table 2. Indicators of forest canopy density model

	Formula	Explanation and practical uses
Advanced vegetation index (AVI)	$\mathrm{AVI} = \left[(B4+1)(256-B3)(B4-B3)\right]^{\frac{1}{3}}$	The use of power degree on NDVI enables AVI to be more sensitive to forest density and physiognomic vegetation indices.
Bare soil index (BI)	$\mathrm{BI} = \frac{(B4+B2)-B3}{(B4+B2)+B3}$	It is the index prepared for analysing soils, in other words it can be used to identify the difference between agricultural and non-agricultural vegetation.
Canopy shadow index (SI)	$\mathrm{SI} = \sqrt{(256-B2)(256-B3)}$	Evaluates the different shadow patterns, based on the structure, age, species distribution etc., by affecting the spectral responses each time.
Thermal index	–	Source of info is the thermal band of thematic mapper sensor (band 6).

*B*2 – green band, *B*3 – red band, *B*4 – near infra-red band, NDVI – normalized difference vegetation index

images must be checked. Then all the bands (except the thermal band) must be normalized by using Eqs 1 and 2:

$$A = \frac{(Y1-Y2)}{(X1-X2)} = \frac{(Y1-Y2)}{(M-2S)-(M+2S)} \quad (1)$$

where:

A – linear transformation,

$Y1$ – maximum value of standardized value,

$Y2$ – minimum value of standardized value,

$X1 = M - 2S$,

$X2 = M + 2S$,

M – mean of values,

S – standard deviation.

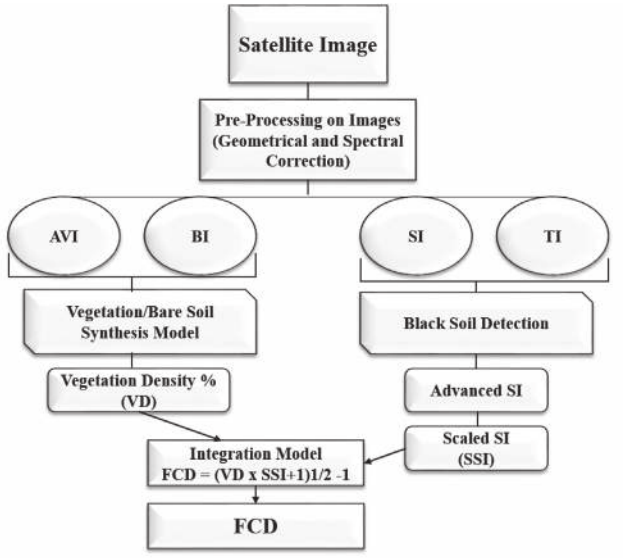

Fig. 2. Methodological flow chart demonstrating different stages of the forest canopy density (FCD) model

AVI – advanced vegetation index, BI – bare soil index, SSI – scaled canopy shadow index, SI – canopy shadow index, TI – thermal index

$$Y = AX + (-AX1 + Y1) \quad (2)$$

where:

Y – normalized data,

X – original value.

According to many researchers who used this method, alone or in comparison with other approaches, the FCD model can be a feasible and accurate approach to the estimation of forest crown canopy density (Table 4).

Detection and separation of bare soil reflectance and plant reflection in a high density forest (more than 70%), no need of training samples during the crown cover density classification are the advantages of FCD model. Also, according to Bonyad (2005), Taefi (2006), Moeinazad Tehrani et al. (2008), and Pakkhesal and Bonyad (2013) the low accuracy of classification in a low and middle density forest can be the disadvantage of FCD model.

It is worth mentioning that the elimination of individual pixels after classification by using a low pass filter (3 × 3 or 5 × 5) can increase the accuracy of classification – average increment 5% (Bonyad 2005; Pakkhesal and Bonyad 2013).

Table 3. Relationship between forest canopy and forest canopy density (FCD) parameters

Index	High FCD	Low FCD	Grassland	Bare land
AVI	high	mid	high	low
BI	low	low	low	high
SI	high	mid	low	low
TI	low	mid	mid	high

AVI – advanced vegetation index, BI – bare soil index, SI – canopy shadow index, TI – thermal index

Table 4. Some researches on the forest canopy density model using different images

Satellite/sensors	References	Resolution (m)
Landsat (TM)	Rikimaru et al. (2002)	30
Landsat (TM, ETM+)	Jamalabad and Akbar (2004)	
Landsat (TM)	Nandy et al. (2003)	
Landsat (GeoCover)	Hadi et al. (2004)	
Landsat 7 ETM+	Joshi et al. (2006)	
IRS (LISS-III)	Azizi et al. (2008)	25
SPOT, ALI	Mahboob and Igbal (2012)	30
Landsat 7 (ETM+)	Pakkhesal and Bonyad (2013)	
Landsat 7 ETM+	Shahvali-Kouhshour et al. (2012)	
Landsat (TM)	Deka et al. (2013)	
Landsat (TM)	Banerjee et al. (2014)	
Landsat 5 (TM) – visible and NIR band	Godinho et al. (2016)	
Landsat 5 (TM) – thermal band	Godinho et al. (2016)	120

TM – thematic mapper, ETM+ – enhanced thematic mapper plus, IRS – Indian remote sensing satellite, LISS-III – linear imaging self-scanning sensor 3, SPOT – Earth observation satellite, ALI – advanced land imager, NIR – near infra-red

DISCUSSION

Main categories of classification

In this study we tried to show the different methods used for crown canopy assessment. All these methods can be divided into two main categories: pixel and object based approaches. The principle of pixel based approaches is based on spectral data derived from pixel cells. As an alternative to the essentially pixel based analysis, the object based method attempts to identify groups of pixels that form discrete objects on the basis of characters that might include overall shape or texture as well as their spectral similarity. Object based methods avoid the need for the complete classification of the whole image, where one has specific interest in one component.

In fact, object oriented methods use segments that are regions specified by one or more yardsticks of homogeneity in one or more dimensions (Hay, Castilla 2008). Using different dimensions like spatial dimensions (distances, neighbourhood, topologies, etc.) is crucial to object oriented methods, making them the most popular methods in recent times, as compared to the usage of pixel based methods (Conchedda et al. 2008).

Biophysical response modelling (FCD method)

Like all models, the FCD model has some advantages and some disadvantages. It is disability to achieve high accuracy in very dense areas and having to use pixel based principles are the biggest disadvantages of this method. On the other hand, modelling with high accuracy and no need of training area establishment (i.e. ground truth) are the most important criteria of FCD that can reduce the time and cost of modelling. So far, many studies have used this approach and almost all of them had acceptable results.

Jamalabad and Akbar (2004) used three sets of thematic mapper and enhanced thematic mapper plus (ETM+) of 1991, 1998 and 2002. FCD from each data set was classified into 5 classes (class 1 – water and clouds, class 2 – no forest, class 3 – low forest, 5–40%, class 4 – middle forest, 41–70%, class 5 – dense forest, 71–100%). The result that came from using ETM+ 2002 was with overall accuracy of 83% and Kappa coefficient 0.78. Finally they used the FCD results of images from the same season in 1991 and 1998 in order to prepare the change detection map for their study area.

Azizi et al. (2008) tested the FCD model using a geometrically corrected image coming from Indian remote sensing satellite (IRS) imagery 2007 of an old growth forest of the north forest division of Iran. The overall accuracy of the IRS images was 84.4% and the Kappa coefficient was 0.783.

After geometric correction (RMSE = 0.5 pixel) of the images and spectral range normalization of the first five bands of Landsat 7, Shahvali-Kouhshour et al. (2012) calculated the four main indicators of FCD using these indicators. They were able to create an advanced shadow index and vegetation density index maps. They used different numbers of classes (3, 4 and 6) to classify the FCD result.

Because their study area was highly heterogeneous and dense, the results showed that the class 3 layer had the highest overall accuracy (62%) and Kappa coefficient 0.30.

Mahboob and Iqbal (2012) used an Earth observation SPOT 5 satellite (2.5 m) and advanced land imager ALI (30 m) for forest crown closure to calculate the forest crown canopy density in Ayubia National Park, Pakistan. A diverse variety of tree species like coniferous and broadleaved tree species are present in this natural environment. Results showed that the crown canopy of the study area using SPOT imagery was between 20 and 65%, and 45–65% with reference to ALI imagery. It was also concluded that SPOT imagery gave better results because of the higher spatial resolution compared to ALI imagery. On the other hand, SPOT was unable to detect the built up and landslide areas and gave them high values, whereas ALI imagery, having a higher spectral resolution compared to SPOT data, was able to detect these areas and give them low values.

Pakkhesal and Bonyad (2013) conducted their study on Landsat ETM+ images in order to classify the crown canopy classes in the Shafarud Area of Guilan. First they prepared a forest density map which included different density classes (bare, 5–25, 25–50, 52–75 and 75–100%). They used the four different indicators of FCD (AVI, BI, SSI, TI) in order to calculate the percentage of canopy density for each pixel. One thematic map came from an orthomosaic aerial photo and was used for the evaluation of FCD accuracy. Results of maximum likelihood classification showed that the FCD map results were close to ground reality (overall accuracy 71% and Kappa coefficient 0.61). Also, the matrix of errors showed that the FCD method is not applicable to areas with high and medium density but it can provide high accuracy for dominant trees and area with low density (lower than 5%).

In overall, the spatial and spectral resolution of images acquired by different sensors brings several advantages to natural resource managers and academic researchers for the classification, monitoring, and management of natural ecosystems. Some of the basic requirements for successful remote sensing-based monitoring can be listed briefly as follows: (*i*) availability of required digital data sources (i.e., imagery, maps, and any other forms of data, (*ii*) collecting up-to-date from the interest area, (*iii*) applying the image processing methodology with respect to the specific characteristics of the study area, (*iv*) producing accurate and useful outputs (e.g., maps and statistics).

Selecting an appropriate method and material with respect to the study area status, aim of study and commercial acceptance can help the mangers and researchers to access easier to their purposes. In case of crown canopy classification, the crown density of the study area and the aim of the study have a significant role which can influence the total accuracy of canopy modelling.

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