# FACTORS RELATED TO TREE COLONIZATION IN RHODOPE MOUNTAINS OF BULGARIA

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# ABSTRACT

This study focuses on causes of tree colonization in Rhodopes Mountains using historical satellite image and Google earth image. Object based image analysis (OBIA) was used to delineate tree crowns from Google Earth image from 2013 and CORONA image from 1965. CPA (crown projected area)-DBH (diameter at breast height), DBH-tree age and CPA-tree age models were generated using forestry inventory data. Canopy cover and tree density were calculated for each sample pot as well. These values were evaluated with field observation and forestry inventory data. From the results of evaluation of OBIA classification maps, it can be concluded that canopy cover was underestimated with the least accuracy in dense forest (NRMSE=55.87%) and in open area sample plots were partially underestimated (NRMSE=23.32 %) while in wood land sample plots were overestimated (NRMSE=24.88%). Tree density was underestimated for dense forest, wood land and open area while average CPA, maximum DBH and maximum age were mostly overestimated.

Canopy cover change rate and tree density change rate were also calculated with delineated tree crowns from present image and historical image. The relation between canopy cover change rate/tree density change rate and tree colonization start time(maximum age) were modelling and found out canopy cover change rate/tree density change rate has significant relation with tree colonization start time (P=$2.878e^{-04}$ and $9.849e^{-04}$*** respectively). They were regarded as indicators of tree colonization start time and tree colonization rate and were used as dependent variables to study factors affecting tree colonization. Terrain (steepness of slope and aspect of slope) and grazing were chosen as explanatory variables. Multivariate linear model is generate to evaluate significance of factors including terrain and grazing.

Surprisingly, it was found that terrain had no significant relation with canopy cover change rate or tree density change rate while only slight grazing and moderate grazing had positive significant relation with canopy cover change rate.


**Key words:** tree colonization, Rhodope mountains, terrain, object based image analysis, grazing

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# 1. INTRODUCTION

## 1.1. Background

Forest cover is an important element of ecosystem. It constitutes a large part of the land area and it contributes more than 80% of biodiversity on the land (Aerts & Honnay, 2011). However, because of disturbances, for example, fire, severe wind, logging, farming and grazing, deforestation became a serious phenomenon which causes the decreasing of biodiversity and do harm to the functioning of forest ecosystems (Aerts & Honnay, 2011; Panayotov, Kulakowski, Laranjeiro Dos Santos, & Bebi, 2011; Seidl et al., 2011). Tree colonization is second succession of forest on abandon pasture land, arable land and logging area and it cause change in land cover change, for example, from grassland or shrub to forest. (Kuiters & Slim, 2003; Myster, 1993). Although deforestation was also the case in many regions of Europe, for instance, Mediterranean area and central Europe which have long history of farming and grazing, spontaneous tree colonization on the farm land and pasture land were observed after agricultural land and pasture land were abandoned in the second half of last century, (Bonet & G. Pausas, 2004; Fernandez et al., 2013; Kienast, Fritschi, Bissegger, & Abderhalden, 1999; Oikonomakis & Ganatsas, 2012; Sheeren et al., 2011). Patterns of tree colonization were found dependent on different regions and tree species (Oikonomakis & Ganatsas, 2012).

Rhodope Mountains are located in southern Bulgaria and northern Greece which is in Mediterranean region. After rural depopulation in recent decades, the pasture land in Rhodope Mountains began to decrease. In the light of a new nature protection law passed in 1967, natural conservation also gained more attention and the forest colonization on abandon pasture land was fastened (Cellarius, 2007). With limited human inhabitation and politically driven land uses, forests were not heavy interrupted and forming large swaths with European beech (*Fagus sylvatica L.*), Scotch pine (*Pinus sylvestris L.*) and Norway spruce (*P. abies Karst*) as dominant species (Kerstin, 2009; Panayotov, et al., 2011). However, around small villages and towns scattered in the Rhodope area, establishing protected areas were delayed because of issues of property ownership and forest restitution (Cellarius, 2007). According to all above, the study area was chosen in Perelik Mountains which is a remote area with Norway spruce as main tree species on the southern part of Rhodope Mountains and became less populated during recent decades (Oikonomakis & Ganatsas, 2012). Therefore, it is an ideal site to study factors affecting tree colonization on disturbed area.

## 1.2. Tree colonization rate

Before analysing the factors influencing tree colonization, it is necessary to study when colonization started which means the oldest tree (maximum tree age) in tree colonization area. However it is more practical to study other characteristics of trees in the field for instance, diameter at breast height (DBH) which were found related to tree age of Norway spruce (Changsheng, Jianfeng, Yongfang, Francis, & Francois, 1998). In addition, RÉDEI & VEPERDI (2001) also pointed out that crown projected area (CPA) was related to DBH. Therefore, in order to predict the start time of tree colonization, the relation between CPA, DBH and tree age of Norway spruce are required to figure out in this study.

Besides CPA and DBH, Hewitt & Kellman (2004) found that canopy openness facilitate seedling survival rate and tree colonization and it can be assumed that tree density change rate (change in number of trees per hectare per year) and canopy cover change rate (change in percentage per year) can be indicators of tree colonization rate and it is also assumed to be the indicators of the start time of tree colonization. In order to prove this point of view, the significances of the relation between canopy cover change rate and maximum tree age and the relation between tree density change rate and maximum tree age should be checked.

### 1.3. Factors influencing tree colonization

Possible factors which affect tree colonization have been discussed including natural factors and human activities, for example, steepness of slope, aspect (Hoersch, Braun, & Schmidt, 2002; Oikonomakis & Ganatsas, 2012), precipitation, temperature (Seidling, Ziche, & Beck, 2012), farming (Harmer, Peterken, Kerr, & Poulton, 2001), logging (Cain & Shelton, 2001) and grazing (Kienast et al., 1999). Interactions also happen between these factors and are different from region to region, for instance, water run-off (interaction between steepness of slope, precipitation and vegetation cover) and human activities influenced by steepness of slope. As a consequence, researches at different scales in various climate regions based on large amount of field studies are needed to add evidence about relationships among these factors and the tree colonization (Oikonomakis & Ganatsas, 2012).

Hamann & Wang (2006) pointed out that climate change is the basic cause affecting the tree expansion. Furthermore, Trant & Hermanutz (2014) observed that different tree species have varied response to climate change and expected that larch (*Larix laricina*) and black spruce (*Picea mariana*) will advance in the future with climate change. However with limited extent of study area with single tree species in Rhodope Mountains, climate change and species composition of forest may not be the main cause.

#### 1.3.1. Terrain

Terrain, including aspect and steepness of slope, was considered as an important factor of tree colonization in previous research (Oikonomakis & Ganatsas, 2012). Temperature, rainfall, solar radiation and soil type which affect where tree colonization occurs are influenced by the effect of terrain. Terrain also interacts with other causes for instance temperature, rainfall and logging. Therefor terrain determines local conditions of mountains for example soil, micro-climate and also determines where tree colonization occurs (Brown, 1994; Luo & Dai, 2013).

Water run-off is one of consequences which are influenced significantly by interaction of steepness of slope, climate, soil type and vegetation cover. Furthermore, run-off will decrease after afforestation (Meuser, 1990; Sensoy & Kara, 2014; Vahabi & Mahdian, 2008). Since the amount of water run-off will increase on steeper slope and decrease on gentler slope, steepness of slope is supposed to be an indication of soil moisture status (Huang, Zhao, & Wu, 2013). When the soil is under drought stress vegetation functions are inhibited (Hoersch et al., 2002; Lendzion & Leuschner, 2008). Therefore, the rate of tree colonization is assumed to be slower on steeper slope.

Solar radiation is a crucial part that affects growth of plants. It was found that forest expansion is related to different solar radiation received on different aspects of slope (Bader & Ruijten, 2008). Michalik (1992) observed that on south-facing slope, beech forest in central Bulgaria is more prompted to expend. The study area in Rhodope Mountains is located in about 40.6N which has more solar radiation on south-facing slope and thus tree colonization is supposed to be faster on south-facing slope.

#### 1.3.2. Grazing

Grazing plays an important role in affecting forest cover change. Kienast et al. (1999) pointed out that forests heavily browsed by animals is likely to be more open and trees grow quicker while mortality is also higher. In Rhodope Mountains, the process of tree colonization is underway after large pasture lands were abandoned. However, grazing evidences were still seen very often, for instance, animal excreta and animal steps. In addition, crowds of sheep, goats and horses can still be seen in study area from time to time.

## 1.4. High resolution historical image

For the purpose of getting historical and current information of CPA of individual tree, high resolution Remote Sensing (RS) images from past and current time are required. With Remote Sensing (RS) images it is possible to monitor tree colonization and it has been widely used to detect forest cover change (Coppin, Jonckheere, Nackaerts, Muys, & Lambin, 2004; Hansen et al., 2013; Oikonomakis & Ganatsas, 2012; Song & Woodcock, 2002). In addition, using RS imagery can overcome the bias resulting from sampling design in ground-based studies especially samples in area which is hard to reach (Groen et al., 2012). Besides high resolution RS images, in order to recognize tree crowns of individual tree, Object based image analysis (OBIA) is also a necessary tool which is one of the most recent and effective method on image classification (Bertani, Rossetti, & Albuquerque, 2013) and it enables deriving CPA from images and predicting the start time of colonization from CPA.

In order to detect the change in forest cover, comparable phenological conditions are required. Considering the slow process of tree colonization the proper time range for monitoring tree colonisation rates would be decades (Holtmeier & Broll, 2005). Thanks to the declassification of CORONA satellites 10 years ago, images with relatively high resolution (highest resolution of 0.6 meter ×0.6 meter) from 1960s to early 1970s are available. Detection of tree colonization from 1960s becomes possible in this research with these low-cost CORONA images (Fowler, 2011; Kuuluvainen & Sprugel, 1996; RÉDEI & VEPERDI, 2001; United States Geological Survey [USGS], 2012).

## 1.5. Research problems

This study aims to identify the factors affecting the rate of tree colonization of Norway spruce in Rhodope Mountains. It is important to figure out the most determining factors for the purpose of conserving and restoring forest after disturbance on abandon pasture land and logging area.

## 1.6. Research objectives

### 1.6.1. Overall objectives

The overall objective is to evaluate the influences of terrain and grazing on tree colonization in the Perelik Mountains, Bulgaria.

### 1.6.2. Specific objectives

- Find relations between stand characteristics (CPA, DBH, age).
- Recognize crown of trees using object based image analyst for different moment; predict and calculate tree characteristics (DBH, age, canopy cover and tree density) from image.
- Evaluate the highest DBH, canopy cover and tree density of each field sample point with field data; evaluate the average age with forest inventory data.
- Test whether relation between canopy cover change rate and maximum age and relation between tree density change rate and maximum age are significant.
- Calculate canopy cover change rate and tree density change rate of each field sample point with historical image and current image.
- Model the relation between canopy cover change rate, terrain and grazing and relation between tree density change rate, terrain and grazing.

## 1.7. Research questions

- Is the accuracy of classification map lower in dense forest?
- Did grazing influence the canopy cover/tree density change per year?
- Did aspect of slope affect the canopy cover/tree density change per year?
- Did steepness of slope affect the canopy cover/tree density change per year?

## 1.8. Hypothesis

- Hypothesis 1

Accuracy of classification result is lower in dense forest than in open forest.

- Hypothesis 2

Canopy cover/tree density change is slower when there is intensive grazing.

- Hypothesis 3

Canopy cover/tree density change is faster on south-facing slope.

- Hypothesis 4

Canopy cover/tree density change is faster on gentler slope.

# 2. METHOD

## 2.1. Study area

Rhodope Mountains is situated in southern part of Bulgaria and the northern part of Greece. The study area of this research is located on Perelik Mountains on the southern part of Rhodope Mountains and the size of study area is about 60 Km$^2$ (Figure 1). Rhodope Mountains is impacted by Mediterranean climate in terms of species composition with dominant tree species of European beech (*Fagus sylvatica L.*), Scotch pine (*Pinus sylvestris L.*) and Norway spruce (*P. abies Karst*) (Kerstin, 2009; Panayotov et al., 2011). The main tree species in the study area is Norway spruce.

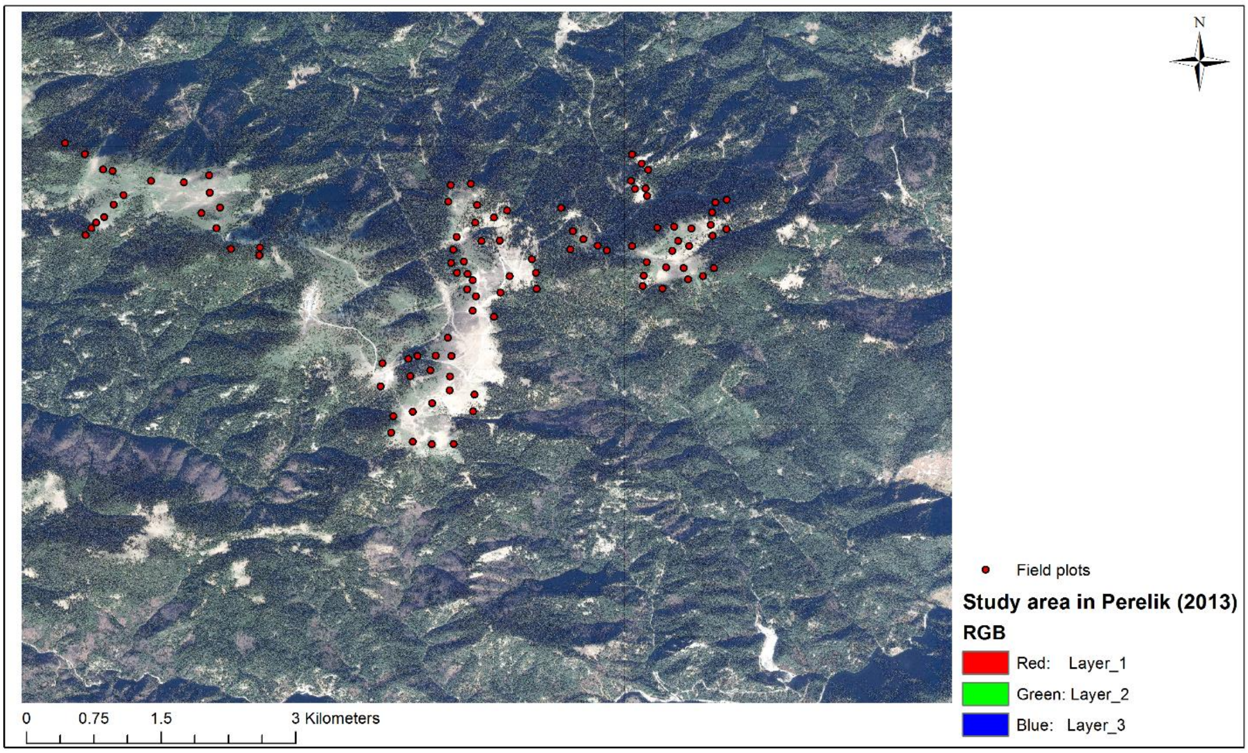



Figure 1 Study area in Perelik with field sample plots

## 2.2. Data sets

### 2.2.1. Forest inventory data sets

Three forest inventory datasets were provided by Tzvetan Zlatanov from Forest Research Institute in Sofia, Bulgaria including two Spruce yield tables and one map (Table 1). The two Spruce yield tables were used to model the relation DBH-CPA and tree age-DBH. The other data set is a map with information of average tree age, DBH and grazing for assessing the accuracy of the age predicted from the Google Earth map from 2013. These datasets were collected in the Perelik Mountain area and same species in recent 5 years with elevations from 1300 to 1900 meters.

Table 1 List of secondary data sets

| Data sets | Samples | Information | Time | File type |
|---|---|---|---|---|
| Spruce yield table A | 76 | CPA and DBH | 2012 | Excel sheet |
| Spruce yield table B | 98 | DBH and tree age | 2012 | Excel sheet |
| Map of study area | - | DBH, tree age and grazing | 2007 | Shapefile |

#### 2.2.2. Fieldwork and field data

Before field work, 100 sample points were selected using stratified sampling to cover different aspects of slope, steepness of slope, canopy cover and grazing classes. Distance between each sample point is at least 50 meters. Considering the accessibility and situation in different parts of the study area, sample points were mostly distributed on the middle part of the study area which is with higher altitude and dense forest or open area can be found easily in this area. A database for collecting data in CyberTracker v3 was also prepared before field work.

In this research, sample points are classified into three land cover classes, dense forest, wood land and open area. Canopy cover larger than 80% (including 80%) is dense forest; canopy cover from 20% to 80% (including 20%) is wood land; canopy cover under 20% is open area. For each sample point on different land cover class, observations were done in different area. Sample plots with radius of 5.6 meter (area about 100 $m^2$) from sample points were created in dense forest. Sample plots with radius of 12.6 meter (area about 500 $m^2$) from sample points were created in wood land and open area. Observations were done in each sample plot with the database in CyberTracker v3 with methods in Table 3 including canopy cover, steepness of slope, aspect, DBH and distance to 5$^{th}$ nearest tree instead of measuring and counting all trees in the plots. In order to measure DBH and number of trees in sample plots with higher efficiency, DBH of five nearest trees from sample point and distance to 5$^{th}$ nearest tree were measured (see Figure 2). Number of trees in sample plots can be estimated from distance to 5$^{th}$ nearest tree using Equation 1 and then tree density can be calculated with Equation 2

$$\text{Equation 1 Number of trees} = r^2 \times \pi \times 5 \div (\pi \times (D_5 \times \text{COS}\ (\alpha \div 180 \times \pi))^2)$$

$$\text{Equation 2 Tree density (number/hectare)} = 10000 \times (5 \div (\pi \times (D_5 \times \text{COS}\ (\alpha \div 180 \times \pi))^2))$$

where $D_5$ is the longest distance to the nearest five trees of sample point (meter), $r$ is 5.6 meters in dense forest or 12.6 meters in wood land and open area, and $\alpha$ is steepness of slope (degree).

Observation about grazing were also recorded as four classes which are non-grazing, slight grazing, moderate grazing and heavy grazing according to the sign of grazing, for example, animal excreta and animal steps. The definition of grazing classes is shown in Table 2.

Logging was found not common in the field so logging will be marked as remarks. Cover of lower layer for example Juniper and grass cover were also marked in remarks. Methods for measuring each characteristic in the field is shown in Figure 2. The data from field work is used to assess the accuracy of image classification.

Table 2 Definition of grazing classes

| Grazing classes | Dense forest | | | Wood land and open area | | |
|---|---|---|---|---|---|---|
| | Excreta (pile) | | Steps (number) | Excreta (pile) | | Steps (number) |
| Non-grazing | 0 | | 0 | 0 | | 0 |
| Slight grazing | (0,5) | or | (0,2) | (0,10) | or | (0,5) |
| Moderate grazing | [5,10) | | [2,5) | [10,20) | | [5,10) |
| Heavy grazing | [10,+∞) | | [5,+∞) | [20,+∞) | | [10,+∞) |

Round bracket means the value is excluded and square bracket means the value is included.

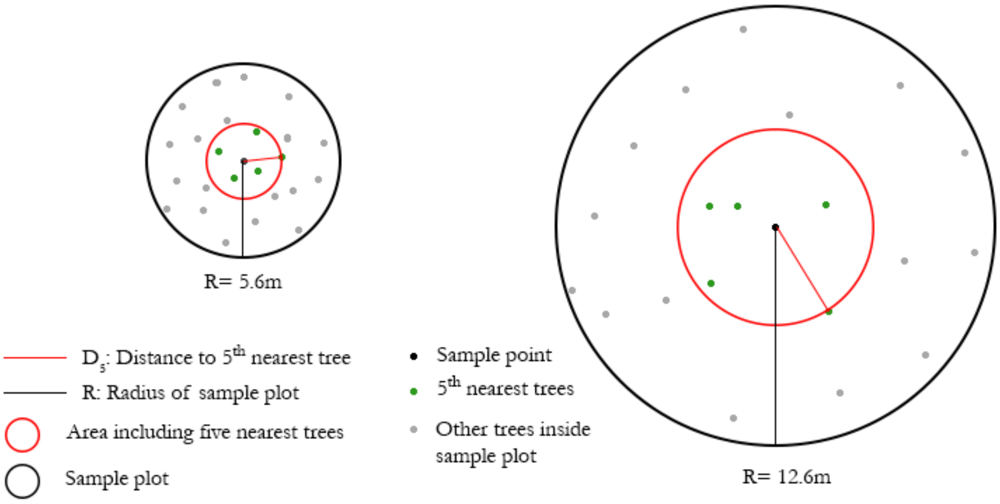


Figure 2 Estimate number of trees in sample plot by measuring distance to 5th nearest tree

Table 3 Methods of measuring each variables

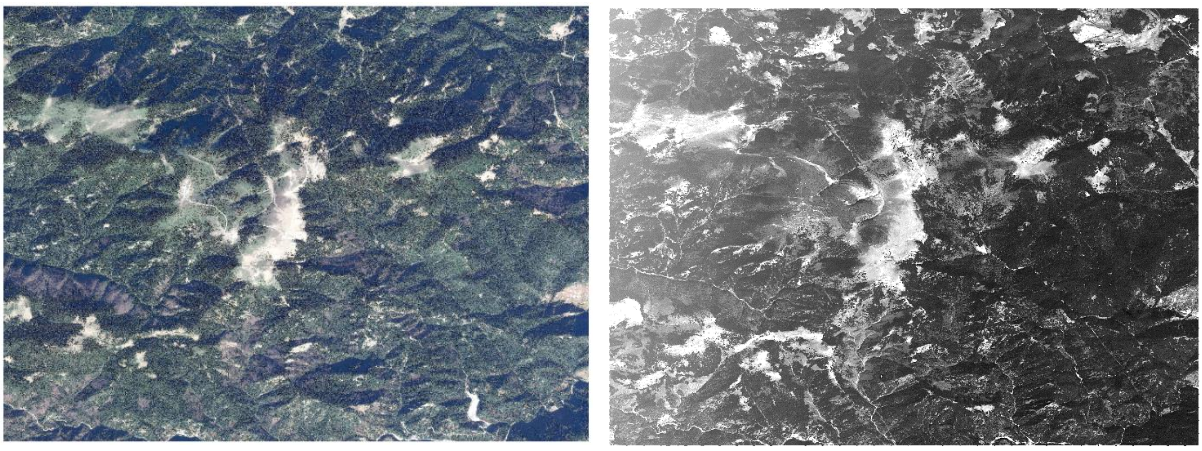
| Variables | Equipments/Materials | Methods |
|---|---|---|
| Canopy cover | Spherical densiometer | Holding it at breast height, estimating the canopy cover by calculating the number of squares in the curved mirror |
| DBH | Caliper | Measure the diameter of the truck on 1.3 meters above the ground |
| Nr. of trees | Tape measure | Measure the distance to the 5th nearest trees |
| Aspect | Compass | Aspect of slope can be read when facing the fall-line of a slope |
| Steepness of slope | Slope meter | - |
| Grazing | - | According to grazing evidence such as steps and excreta of animals |

### 2.3. Imagery

For detection of tree colonization, historical images and the latest image of study area with high resolution are required, which enable identification of individual trees. In this research, images are from CORONA satellite and Google Earth. Nine CORONA images and two Google Earth images were selected based on time, resolution and covering area as shown in Table 4. Compared all the images from USGS and Google Earth images, images of 1965 and 2013 were chosen for this study since they have higher resolution and less cloud cover on the study area. The only weak point of the image of 1965 is that the image is brightened gradually because the study area is on the edge of the whole aerial photo (Figure 3 (b)). This have to be fixed when setting the criteria in object based image classification.

Table 4 Selected aerial photos

| Acquisition Date | Resolution | Satellite | Source | Remarks |
|---|---|---|---|---|
| 10/2/1965 | 0.6 × 0.6 meter | CORONA | USGS | Selected image |
| 11/3/1965 | 2.7 × 2.7 meter | CORONA | USGS | Lower resolution |
| 9/30/1968 | 2.7 × 2.7 meter | CORONA | USGS | Lower resolution |
| 9/26/1969 | 2.7 × 2.7 meter | CORONA | USGS | Lower resolution |
| 7/12/1975 | 0.6 × 0.6 meter | CORONA | USGS | Covering with Clouds |
| 9/14/2011 | 0.8 × 0.8 meter | Ikonos | Google Earth | - |
| 10/26/2013 | 0.8 × 0.8 meter | Ikonos | Google Earth | Latest image |



a b

Figure 3 a. Google Earth image of 2013; b. CORONA image of 1965

Google Earth image from 2013 was geo-referenced with ground control points and projected to WGS-1984-UTM-35N. The CORONA image from 1965 was first geo-referenced with coordinates information from USGS which includes the four corners of the whole image. The image from 1965 still shift for about 1 kilometre compared to the image from 2013 and according to information about the metadata, there may be ten miles error with the metadata corner coordinates (USGS Earth Resources Observation & Science Center [EROS], 2002). Therefore the image of study area from 1965 was geo-referenced again with roads on Google Earth image from 2013, supposed that the roads on study area did not have great changes.

Terrain maps include a slope map and an aspect map generated from ASTER global DEM image in 2011 with resolution of 1 arc-second acquired from Earth Explorer in USGS website. The slope map and the aspect map were created with Slope tool and Aspect tool from Spatial Analyst tools of ArcGIS 10, respectively. Aspect derived from the aspect map was from 0° to 360 ° yet it is not ready to use in modelling. In order to show orientation more directly, northness are calculated with Equation 3

Equation 3 $\text{Northness} = \cos((\text{Aspect map} \times \pi) \div 180)$ (Wallace & Gass, 2008, p. 7)

where the range of northness is from -1 to 1 indicating that 1 is north and -1 is south.

### 2.3.1. Aerial image classification using OBIA

Before classifying the images with OBIA, the CORONA image of 1965 was firstly resampled to the same resolution as the Google Earth image of 2013 (0.8 × 0.8 meter). Secondary, both of the images were filtered in Erdas Imagine 2013 with the 3 × 3 low pass which was to remove noise and distinction the objects on the images. In order to obtain the value of CPA of each tree from images, the images were classified to generate classified maps using OBIA in eCognition V9.0. To recognize the tree crowns on the whole image of 2013, a small area about 3000 pixels × 3000 pixels including some field sample points was used to find out the classification criteria for the whole image. For classifying the gradually brightened image of 1965, the image was divided visually into four parts according to the differently brightened area. Since different criteria are required for different image, two set of criteria were created for images of 1965 and 2013 as shown in Table 5.

Table 5 Criteria for image of 1965 and 2013

<table>
<tr><th rowspan="2" colspan="3">Time</th><th rowspan="2">2013</th><th colspan="5">1965</th></tr>
<tr><th></th><th>Part I</th><th>Part II</th><th>Part III</th><th>Part IV</th></tr>
<tr><td rowspan="14">Criteria</td><td>Segmentation</td><td>Scale parameter</td><td>8</td><td colspan="5">5</td></tr>
<tr><td rowspan="9">Shadow masking</td><td rowspan="3">Brightness (shadow)</td><td rowspan="3">[0,52.5]</td><td>Upper part</td><td>(0,110]</td><td>(0, 78]</td><td>(0, 75]</td><td rowspan="3">(0, 27]</td></tr>
<tr><td>Middle part</td><td>(0, 90]</td><td rowspan="2">(0, 45]</td><td rowspan="2">(0, 35]</td></tr>
<tr><td>Lower part</td><td>(0, 68]</td></tr>
<tr><td rowspan="3">Brightness (Forest)</td><td rowspan="3">(52.5, 100]</td><td>Upper part</td><td>(110, 115]</td><td>(78, 87]</td><td>(75, 82]</td><td rowspan="3">(27, 62]</td></tr>
<tr><td>Middle part</td><td>(90, 95]</td><td rowspan="2">(45, 72]</td><td rowspan="2">(35, 60]</td></tr>
<tr><td>Lower part</td><td>(68, 80]</td></tr>
<tr><td rowspan="3">Brightness (Bare land)</td><td rowspan="3">(100, +∞)</td><td>Upper part</td><td>(115, +∞)</td><td>(87, +∞)</td><td>(82, +∞)</td><td rowspan="3">(62, +∞)</td></tr>
<tr><td>Middle part</td><td>(95, +∞)</td><td rowspan="2">(72, +∞)</td><td rowspan="2">(60, +∞)</td></tr>
<tr><td>Lower part</td><td>(80, +∞)</td></tr>
<tr><td>Watershed trasformation</td><td>Length factor</td><td>10</td><td colspan="5">8</td></tr>
<tr><td>Morphology</td><td>Mask</td><td>10</td><td colspan="5">10</td></tr>
<tr><td rowspan="2">Remove undesired objects</td><td>Roundness</td><td>[1, +∞)</td><td colspan="5">[1, +∞)</td></tr>
<tr><td>Area</td><td>(-∞,7)</td><td colspan="5">(-∞,7)</td></tr>
</table>

- Segmentation: The scale parameter determine the maximum allowable heterogeneity in the segmented object.
- Shadow masking: Value inside the bracket mean the brightness range of objects for each class (round bracket means value not included; square bracket means value included).
- Watershed transformation: The largest crown diameter observed in the field which is 8 meters in the field and 6.5 meters from image of 1965. The length factor is the largest crown diameter converted in to pixels according to pixel size of image.
- Morphology: The size of a circular mask which was used to smoothing the boundaries of the segments.
- Roundness: Value inside the bracket mean the roundness range of objects that should be removed (round bracket means value not included; square bracket means value included). The smaller the roundness, the rounder the object.
- Area: Value inside the bracket mean the area range of objects on pixel level that should be removed (round bracket means value not included; square bracket means value included).

In image 2013, tree crowns detected from the first segmentation with crown diameter larger than 8 meters were divided into two or more tree crowns, which was controlled by the watershed transformation function. The criteria of 8 meters was from the largest tree observed from the field. However, there is no field observation of largest tree in 1965 so the largest tree crown was recognized visually and measured in Arcmap which is about 6.5 meters. For both images, trees with crown diameter smaller than 2 meters were excluded.

Buffer zone was made for every field sample point. For dense forest the buffer zone was made with radius of 5.6m (area about 100m²) from the sample point; wood land and open area are with radius of 12.6m (area about 500m²) from the sample point. With the buffer zones, object bases image classification map of 2013 and 1965, canopy cover, tree density, canopy cover change rate and tree density change rate can be calculated on each buffer zone.

### 2.3.2. Accuracy assessment

An error matrix of the object based image classification map of 2013 and 1965 were generated with the observations from the field based on two classes, tree crown area and non-tree crown area. Before assess the accuracy of classification map of 1965, maximum tree age predicted from ground measurement of maximum DBH in sample plots which are larger than 49 are regarded as tree crown area in 1965. Producer accuracy, user accuracy and overall accuracy were evaluated and illustrated in the error matrix. Producer accuracy is the proportion of the crowns in the field that are correctly identified by OBIA. User accuracy is the proportion of the crowns identified by OBIA that are indeed crowns in the field. Overall accuracy is the proportion of tree crowns that are classified correctly(Olofsson, Foody, Stehman, & Woodcock, 2013).

To evaluate the tree crowns recognized with OBIA, average CPA, maximum DBH, maximum age, canopy cover, tree density of sample plots were used as evaluation data. For average CPA, maximum DBH and maximum age, sample plots with no tree in field data and no tree on classification map of 2013 were excluded when field value and image value were used to model to find out whether image value had significant relation with field value. In addition, a map with forest inventory data was used to evaluate the average age for the whole study area in 2013. Average age predicted from the average CPA which was calculated for each small area in the map was compared with average age of same area in the map. Scatter plots and NRMSE (normalized root-mean-squared error) will be used to know the difference between predicted value and field value. NRMSE of prediction was calculated with Equation 4

$$\text{Equation 4 NRMSE} = \sqrt{\sum_{t=1}^{n}(\hat{y}_t - y)^2 \div n} \div (\hat{y}_{max} - \hat{y}_{min})$$

where $\hat{y}$ is prediction value and y is true value from field data and forestry inventory data.

## 2.4. Statistical analysis

### 2.4.1. Variables selections

As discussed in Chapter 1, canopy cover change rate and tree density change rate were assumed to be indicators of start time of tree colonization. Thus, these two tree characteristics can be the independent variables if relation between canopy cover change rate/tree density change rate and start time of tree colonization. For the study area in this research, evidence of grazing was most obvious while human activities were barely found. Therefore, grazing, steepness and aspect of slope were re to be the explanatory variables in the linear regression as discussed in Chapter 1.

Before doing multivariate linear regression, collinearity is necessary to check among selected explanatory variables. Besides grazing which is a categorical variable, the other two variables, steepness of slope and northness, are continuous variables. Therefore, Pairwise Pearson's correlation coefficient of two continuous variables was generated in R Studio using Stats Package and VIFs (variance inflation factor) of two continuous variables were calculated with Equation 5

$$\text{Equation 5 } VIF_i = 1 / (1-R_i^2)$$

Where $R_i^2$ is the $R^2$ of a model using one of the independent variables ($X_i$) as dependent variable and the other explanatory variables as independent variables. When the correlation coefficients is higher than 0.5 and/or VIF is higher than 10, collinearity may exist among explanatory variables and one of the variables should be remove for lower VIF and calculate the correlation coefficients and VIF again. However, variable should be removed with caution and consider the purpose of study.

Two bivariate linear regressions were performed where grazing is independent variable and steepness of slope or northness is dependent variable. The first class of grazing (non-grazing) was regarded as default value. When the P value of a grazing class is higher than 0.05 which means steepness of slope or northness has significant difference between that grazing class and default class (non-grazing), collinearity may be a problem when modelling.

After having decided on the explanatory variables, it is necessary to visualize distribution of exploratory data before begin data analysis. Explanatory data analysis of steepness of slope, northness and grazing were performed in frequency histogram graph.

### 2.4.2. Data preparation

#### 2.4.2.1. Data from classified image

After created the classification maps of 2013 and 1965, canopy cover change rate and tree density change rate of each sample plot can be calculated with tree crowns delineated from the image by OBIA using Equation 6 to Equation 9.

$$\text{Equation 6 Canopy cover (\%)} = CPA_T \div r^2 \times \pi$$

$$\text{Equation 7 Tree density (number/hectare)} = N \div r^2 \times \pi \times 10000$$

$$\text{Equation 8 Canopy cover change rate (\%/year)} = CC \div Age_{max}$$

$$\text{Equation 9 Tree density change rate (number/hectare/year)} = TD \div Age_{max}$$

where $CPA_T$ is the total area of tree crowns delineated on image, $r$ is 5.6 meters in dense forest or 12.6 meters in wood land and open area, $N$ is number of trees delineated inside sample plots on image, $CC$ is canopy cover of each sample plot calculated with Equation 6, $TD$ is tree density of each sample plot calculated with Equation 7, and $Age_{max}$ is the maximum tree age predicted from the largest CPA in each sample plot using model tree age-CPA. Histograms of change rate of canopy cover and tree density were generate and were divided into six classes and five classes respectively in R Studio. Canopy cover change rate and tree density change rate were also shown spatially on classification map of 2013 with five different colors presenting five classes classified.

#### 2.4.2.2. Field data

Field data was converted into the right dimensions for the subsequent analysis. The distance to the 5th nearest tree was converted to tree density with Equation 3.

In order to make it comparable to CPA derived from image, canopy cover and distance to the 5th nearest tree was converted to average CPA with Equation 10

$$\text{Equation 10 Average CPA (m}^2\text{)} = \text{Canopy cover} \div 100 \div (5 \div (\pi \times (D_5 \times COS(\alpha \div 180 \times \pi))^2))$$

where $D_5$ is the longest distance to the nearest five trees of sample point (meter), and $\alpha$ is steepness of slope (degree).

#### 2.4.3. Linear regression modelling

The relations DBH-CPA and tree age-DBH were bootstrapping modelled using two Spruce yield tables of forest inventory data from 2012. There was no data set including tree age and CPA together therefore DBH in the Spruce yield table A was converted to tree age using the model tree age-DBH to create a new data set. For each dataset, observations were randomly selected with replacement to create new datasets (same size as the original dataset) for 100 times and do linear regression for each new datasets in R studio. Average slope, average intercept and the average p value of 100 models are the coefficients of the final model. Maximum, minimum, average and standard deviation value of $R^2$ and maximum p value were calculated to show the goodness of fit and the significance of the model. With the DBH-CPA and age-DBH model, DBH and age of individual tree can be predicted from the CPA.

After maximum tree age was predicted with maximum DBH from ground measurement using age-DBH model, relation between canopy cover change rate and maximum age predicted from ground measurement was modelled as well as relation between tree density change rate and maximum age predicted from ground measurement. These two models were generated to discover whether relations are significant. For all models above, $R^2$ and RMSE were used to evaluate the model. $R^2$ of each model was generated in R studio and NRMSE of prediction was calculated with Equation 4.

A table with explanatory variables (steepness of slope, northness, grazing) and response variable (canopy cover change per year and tree density change per year) was created for multivariate linear model in R Studio after detecting collinearity, then use stepwise to select most significant variables. With this model, determinant factors with significant influences on tree colonization were discovered.

# 3. RESULTS

## 3.1. Linear regression models to predict tree age

According to Figure 4 and Table 6, relation between CPA, DBH and tree age are significant (α=0.05) but average $R^2$ of these three models are relatively low. The highest average $R^2$ is from model tree age-DBH as well as the highest maximum $R^2$, which are 0.590 and 0.767, respectively. The low $R^2$ value of model indicates that the model only explains part of the dependent variables. When using the bootstrapping to model the relations, 100 models were generated for each relations therefore the maximum P value among 100 models can estimate the significance of the relation in most conservative way. The maximum P value of three relations are all lower than α=0.05 and thus CPA, DBH and tree age are significant related (α=0.05).

From Figure 4 it is obvious that the first and the third scatter plots are similar on distribution of the points but model tree age-CPA with higher $R^2$ than model DBH-CPA, which is possibly because they were based on the same data set and model tree age-DBH has higher $R^2$. According to the average RMSE of three models, model tree age-CPA has the lowest RMSE and it means that the actual value are more close to the predicted value.

Considering all this analysis, these three models can be used to predict the tree age from CPA derived from the images but it will cause some error to the result.

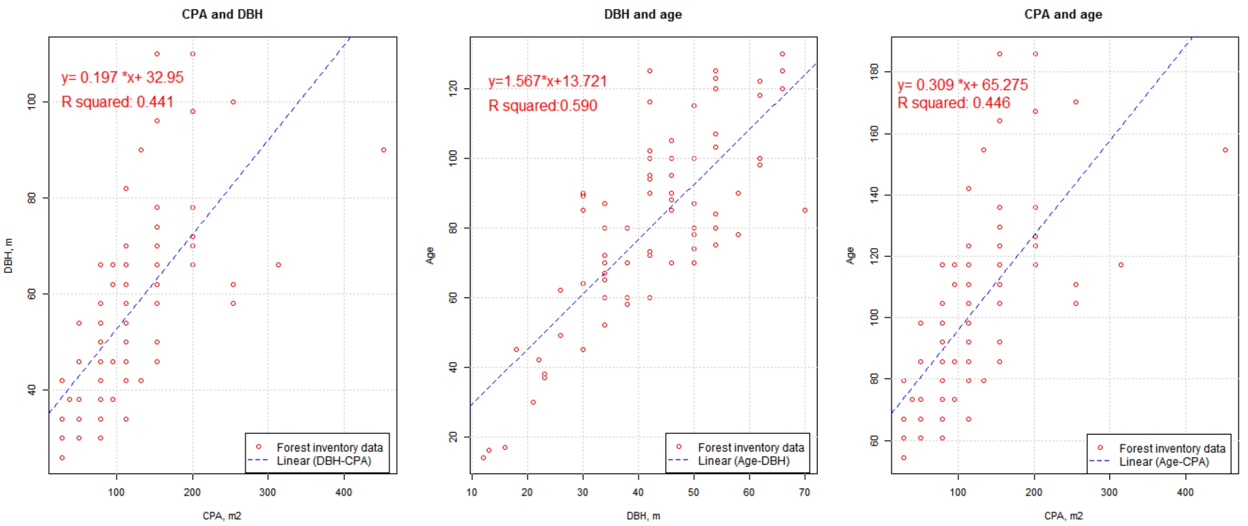



Figure 4 Scatter plots of three models

Table 6 Coefficients, $R^2$ and RMSE of three models

| Models | | DBH-CPA | Tree age-DBH | Tree age-CPA |
|---|---|---|---|---|
| P value | Average | 7.50E-10*** | 2.70E-08*** | 4.30E-08*** |
| | Maximum | 3.84E-10*** | 1.41E-08*** | 1.96E-08*** |
| $R^2$ | Average | 0.441 | 0.590 | 0.446 |
| | Standard deviation | 0.058 | 0.073 | 0.059 |
| | Max | 0.616 | 0.767 | 0.644 |
| | Min | 0.308 | 0.399 | 0.317 |
| Slope | Average | 0.197 | 1.567 | 0.309 |
| Intercept | Average | 32.950 | 13.721 | 65.275 |
| NRMSE | Average | 16.660% | 18.535% | 16.614% |

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

## 3.2. Object based image classification

### 3.2.1. Classification maps

Objects were recognized on aerial photos of 1965 and 2013 and classified into forest area and non-forest area according to the brightness of the object (Figure 5 and Figure 6). The whole study area was classified for the image of 2013 but for the image of 1965 only the area with sample plots were classified.

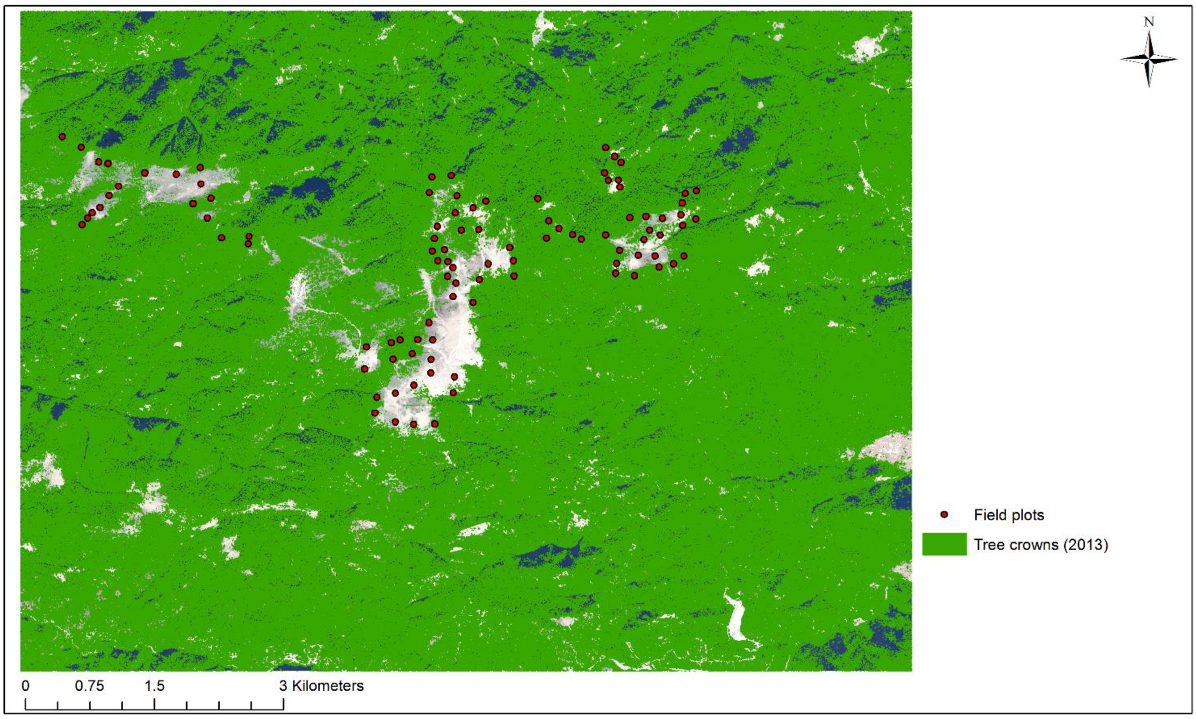



Figure 5 Forest area in 2013 (study area)

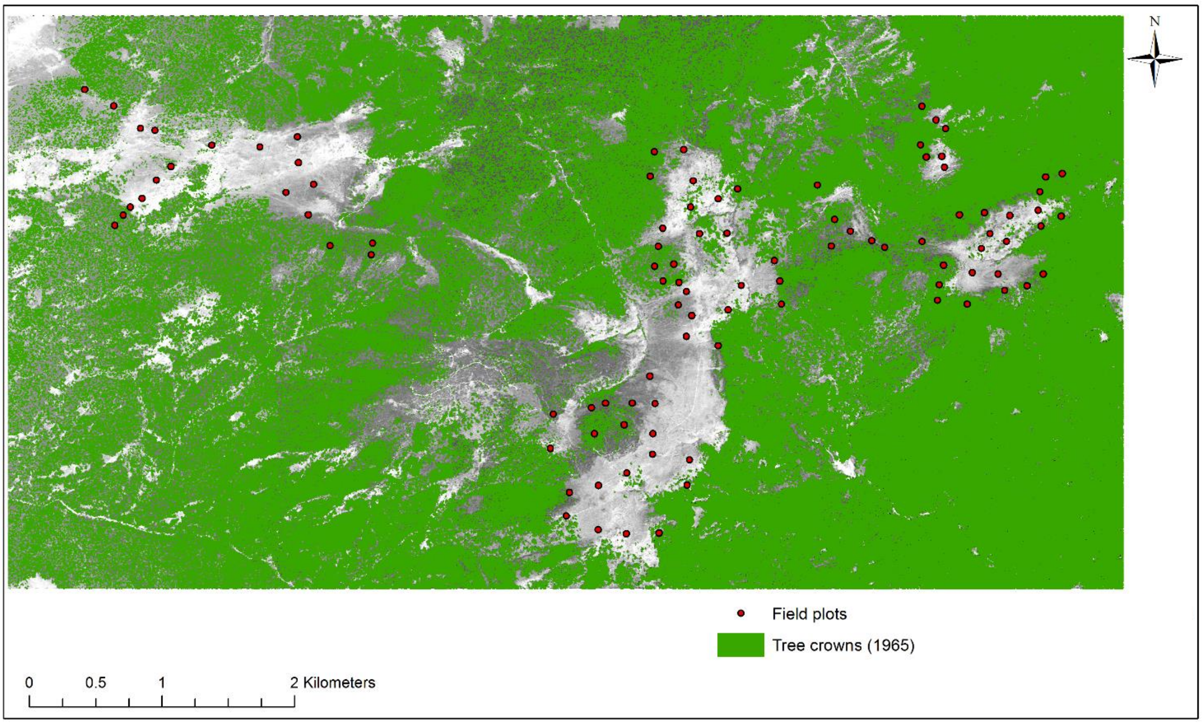


Figure 6 Forest area in 1965 (sample area)

### 3.2.2. Accuracy assessment

#### 3.2.2.1. Error matrix of presence and absence of trees on classified images

As shown in Table 7, producer accuracy and user accuracy of each class are all higher than 70% and overall accuracy is 90%. For the purpose of predicting age from the tree crown delineated on the classified image, the accuracy of each sample plots on image are the user accuracy, which are 89.74% and 90.91% on tree crown area and non-tree crown area, respectively.

The classification map of 1965, however, has lower accuracy (Table 8). For the sample plots with tree crown on classification map, the user accuracy is only 64.29%, which may cause error when continue to derive tree age, canopy cover and tree density from the image.

Table 7 Error matrix of the classification map of 2013

| | | Field data | | | |
|---|---|---|---|---|---|
| | | Tree crown | Non-tree crown | Total | User's accuracy |
| Classification map | Tree crown | 70 | 8 | 78 | 89.74% |
| | Non-tree crown | 2 | 20 | 22 | 90.91% |
| | Total | 72 | 28 | 100 | |
| | Producer's accuracy | 97.22% | 71.43% | | |
| | Overall accuracy | 90% | | | |

Table 8 Error matrix of the classification map of 1965

| | | Field data | | | |
|---|---|---|---|---|---|
| | | Tree crown | Non-tree crown | Total | User's accuracy |
| Classification map | Tree crown | 36 | 20 | 56 | 64.29% |
| | Non-tree crown | 6 | 38 | 44 | 86.36% |
| | Total | 42 | 58 | 100 | |
| | Producer's accuracy | 85.71% | 65.52% | | |
| | Overall accuracy | 74% | | | |

#### 3.2.2.2. Evaluation of tree characteristics from images

As shown in previous results about accuracy of classification map of 2013 in Table 7, ten sample plots were incorrectly classified. From a small area of object based image classification map in Figure 7, it is obvious that shadow in dense forest were much darker than in open area and thus some tree crowns in dense forest were likely to be assigned as shadow area when removing the shadows in open area. Furthermore, some of the boundaries of tree crown were not distinguishable enough in less dense forest and thus some tree crowns in less dense forest tended to be regarded as open area when removing the bare land area and some Junipers or other shrubs in open area tended to be regarded as tree crown, which resulted in incorrect classification of sample plots in less dense forest or open area. Furthermore, tree characteristics, for instance, average CPA, maximum DBH, maximum age and average age have no meaning in sample plots where there were no tree. However, canopy cover and tree density of sample plot still have meaning when there were no tree. Therefore, only field value of sample plots where trees were observed were used to evaluate the average CPA, maximum DBH, maximum age and average age predicted from the classification map of 2013 and thus twenty eight sample plots were excluded; sample plots which were correctly classified as non-tree crown area were included when evaluated the canopy cover and tree density calculated from the classification map of 2013 and thus eight sample plots were excluded.

From Table 9, it is noticeable that only field value of canopy cover and tree density had significant relation with the actual value. For average CPA, maximum DBH, maximum age and average age, P value were higher than $\alpha=0.05$, which mean there were no significant relation between image value and field data of these tree characteristics.

All the R2 of the linear regressions between image value and field value were relatively low which are unexpected because low R2 means that the goodness of fit in the linear model is low and value predicted from image value may have error. Tree density had lowest NRMSE which was 19.395% and average CPA had highest NRMSE which was 84.348%. In addition, the range of average age in forest inventory data was much larger than the average age from image according to Figure 13 and NRMSE was second-highest with the value of 51.700%.

Compare to the 1:1 line in Figure 8, Canopy cover calculated from recognized tree crowns within each sample plots were mostly underestimated. Sample plots in dense forest were underestimated (NRMSE=55.873%) and in wood land sample plots were partially underestimated (NRMSE=23.316%) while in open area sample plots were overestimated (NRMSE=19.439%). According to Figure 9, tree density tended to be underestimated more consistently.

From Figure 10 to Figure 12, it is shown that average CPA, maximum DBH and maximum age were mostly overestimated in all three kinds of land cover. This may be result from overestimated tree crowns in the classification map. As shown in Figure 7, a bunch of small trees in dense forest tended to be classified as one tree as well as trees on more open area which tended to combine the bare land and thus the tree crowns were overestimated in both situation.

In Figure 11 and Figure 12, it is noticeable that the distribution of points was similar in two scatter plots. It is because the maximum age from image and from field observation are predicted with the maximum DBH from image and from field observation using model tree age-DBH.

Considering the P value, R2, NRMSE in Table 9 and scatter plots, average CPA, maximum DBH, maximum age and average age were not well estimated from the image.

Table 9 Coefficients, R2 and NRMSE of linear regression of image value-field value of each characteristics

| Field value-Image value | Canopy cover | Tree density | Average CPA | Maximum DBH | Maximum age | Average age (compared to forestry inventory data) |
|---|---|---|---|---|---|---|
| Slope | 0.786 | 2.503 | 0.101 | -0.279 | -0.216 | 0.017 |
| P value | 1.639E-09*** | 1.739E-07*** | 0.159 | 0.163 | 0.211 | 0.964 |
| $R^2$ | 0.334 | 0.263 | 0.028 | 0.028 | 0.022 | 2.0E-06 |
| NRMSE | 30.322% | 19.395% | 84.348% | 29.556% | 30.076% | 51.700% |

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

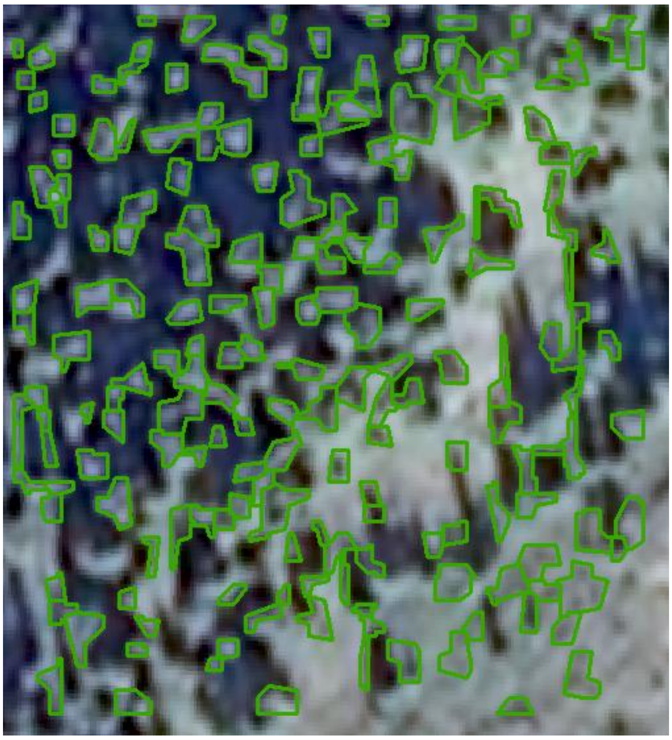


Figure 7 Tree crowns delineated in dense forest and open are on image of 2013

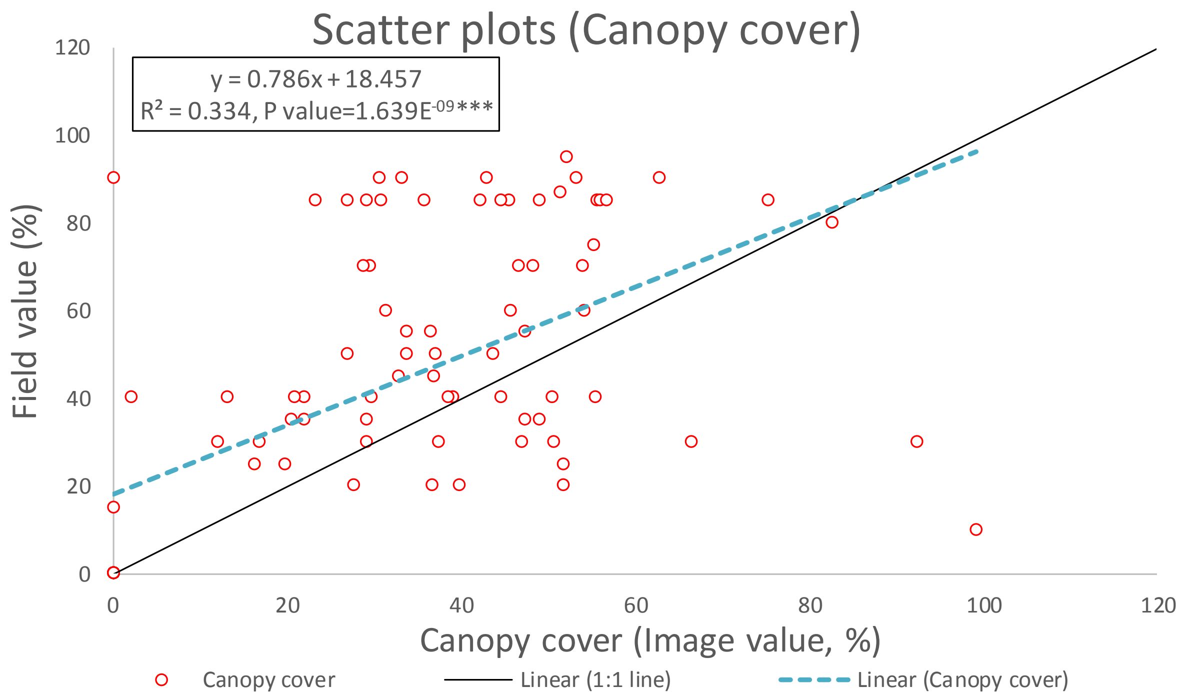



Figure 8 Scatter plots of canopy cover (image value of 2013 and field data)

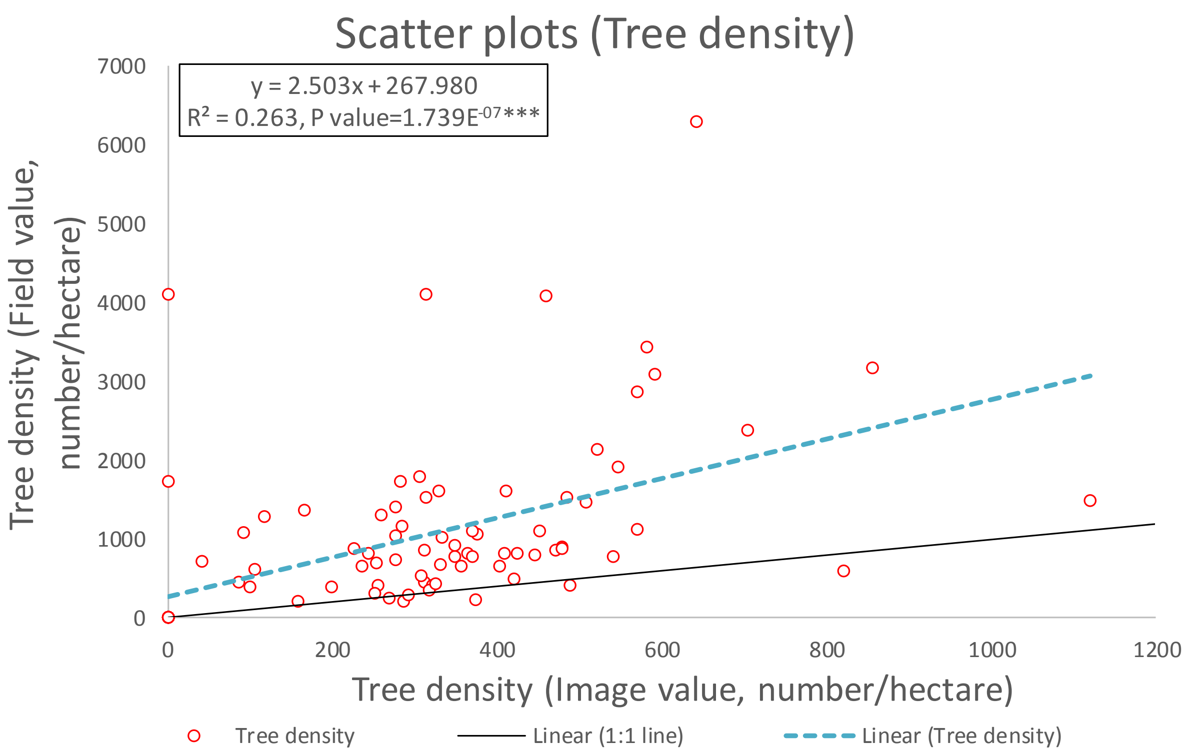



Figure 9 Scatter plots of tree density (image value of 2013 and field data)

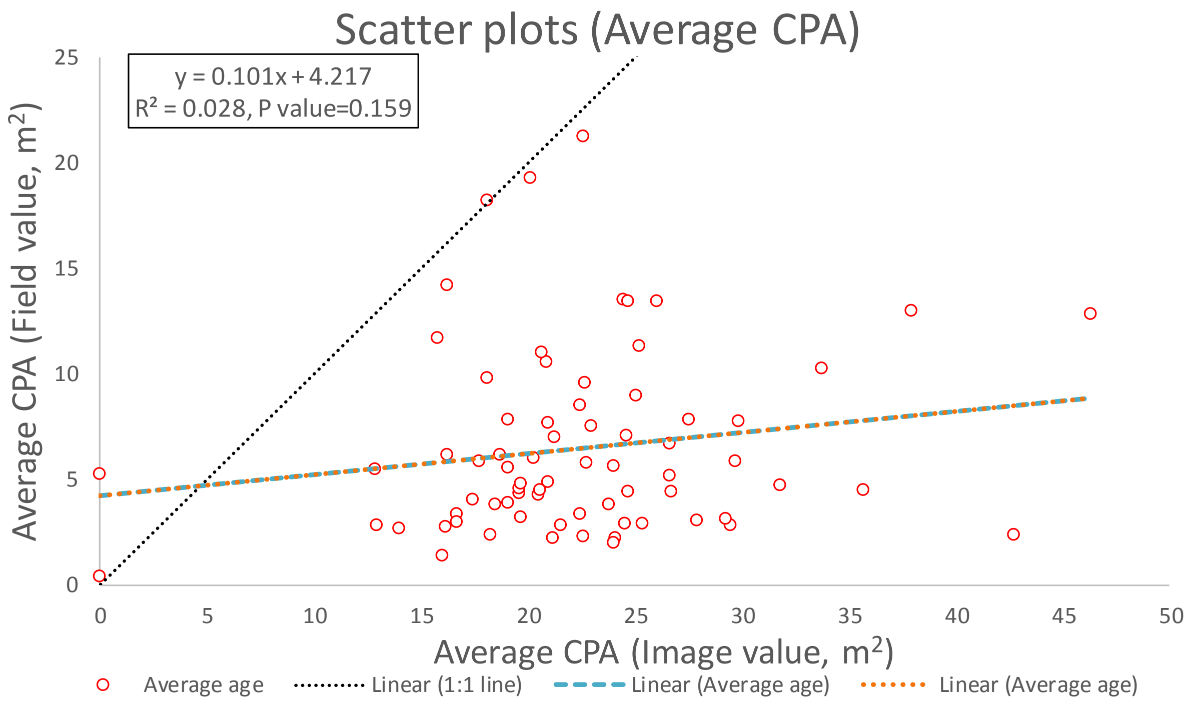



Figure 10 Scatter plots of average CPA (image value of 2013 and field data)

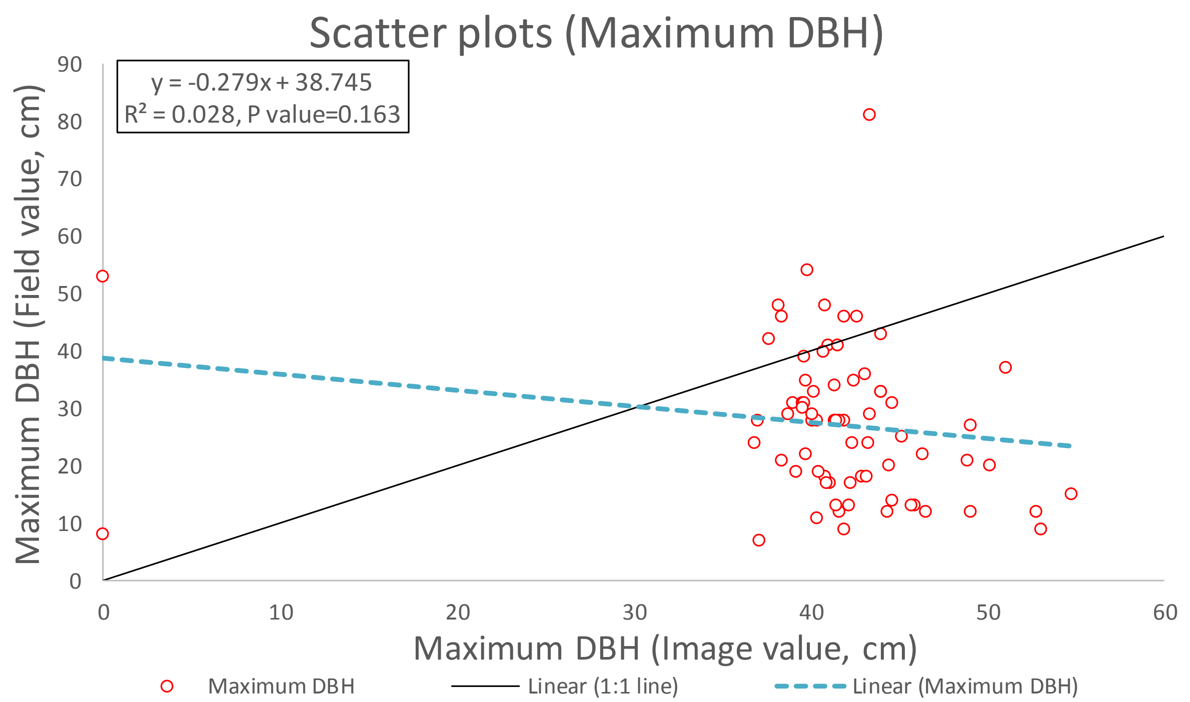



Figure 11 Scatter plots of maximum DBH (image value of 2013 and field data)

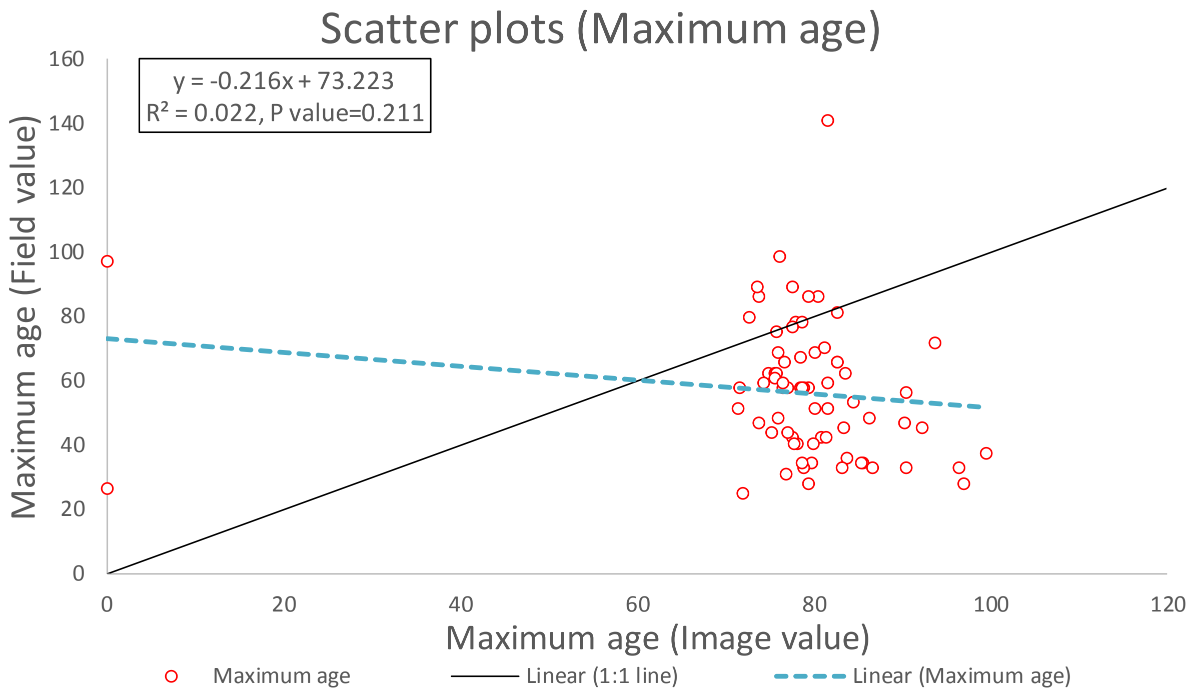



Figure 12 Scatter plots of maximum age (image value of 2013 and field data)

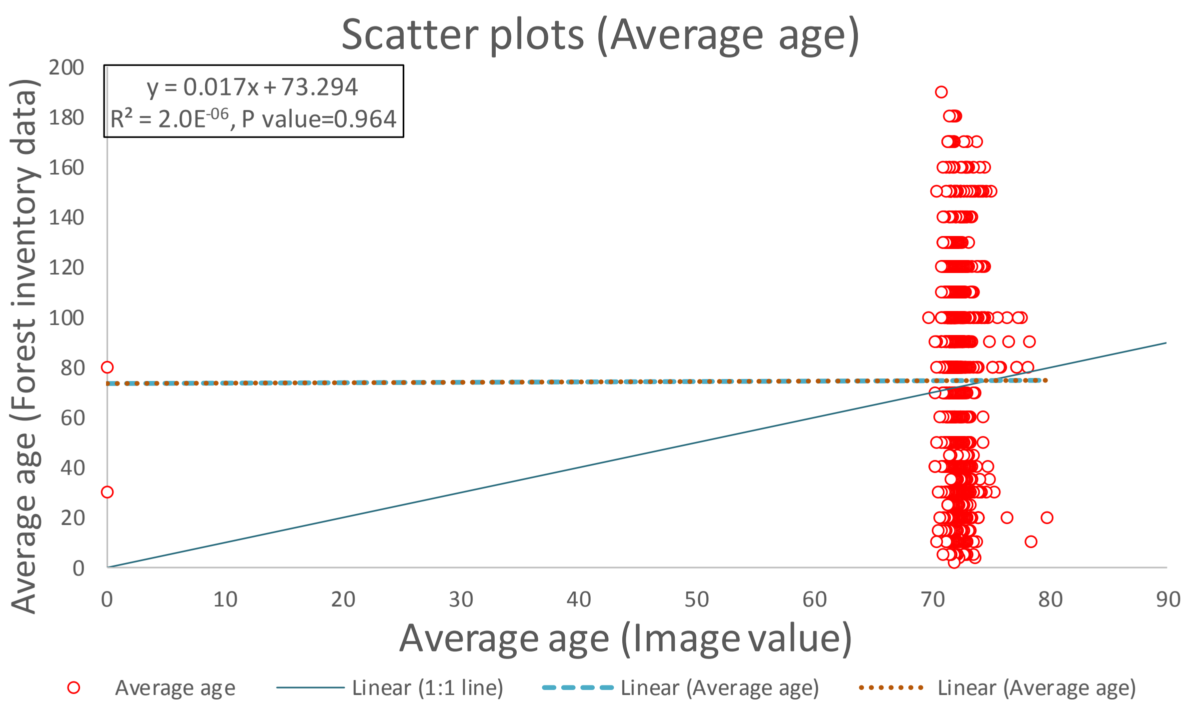



Figure 13 Scatter plots of average age (image value of 2013 and forest inventory data)

### 3.2.3. Change rate of canopy cover and tree density

As shown in Figure 14 and Figure 15, different colors represented different range of value. From Figure 14, it is notable that most of sample plots had canopy cover change rate with range from -1 to 1 and they evenly distribute on sample area. As can be seen in histogram of canopy change rate (Figure 16(a)), canopy cover in 49 sample plots had increased and 51 sample plots had decreased.

As illustrated in Figure 15, the change rate of tree density mostly fell into range from -10 to 10 and they also evenly distribute on sample area. As shown in histogram of tree density change rate (Figure 16(b)), half of sample plots had increased in tree density and the other half had decreased.

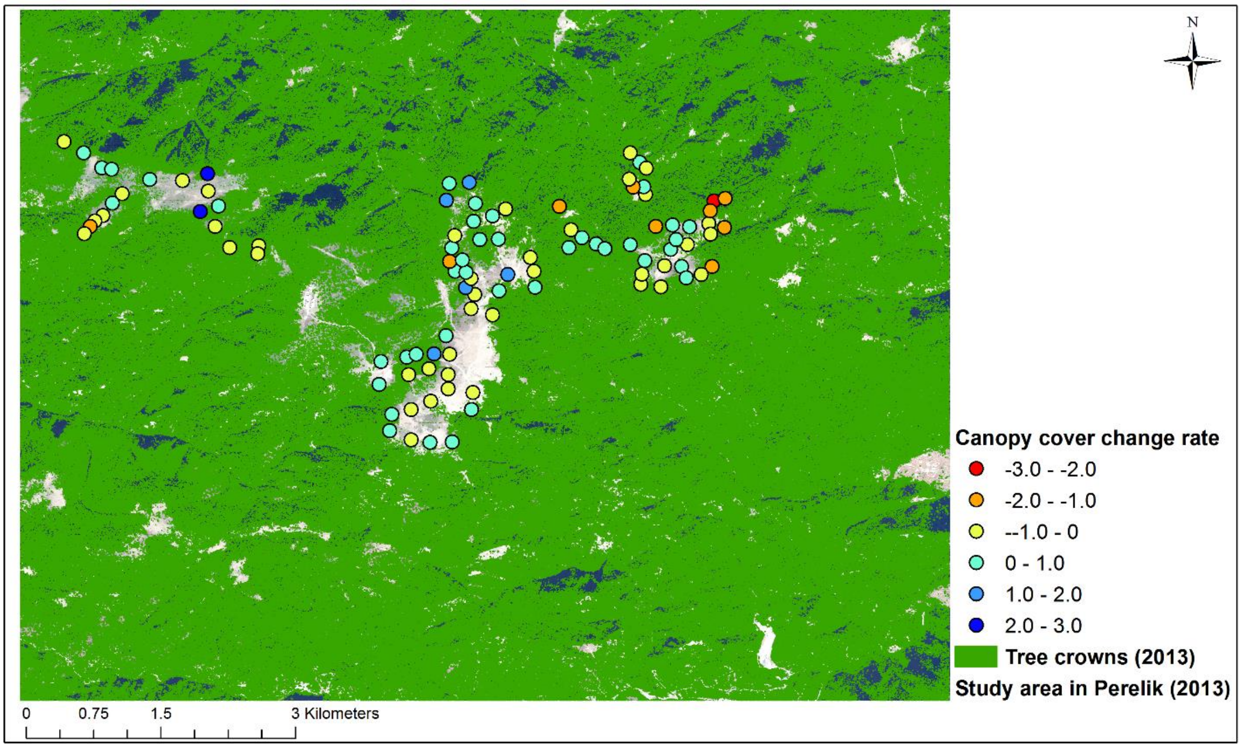



Figure 14 Canopy cover change rate of each sample plot shown spatially on classification map of 2013

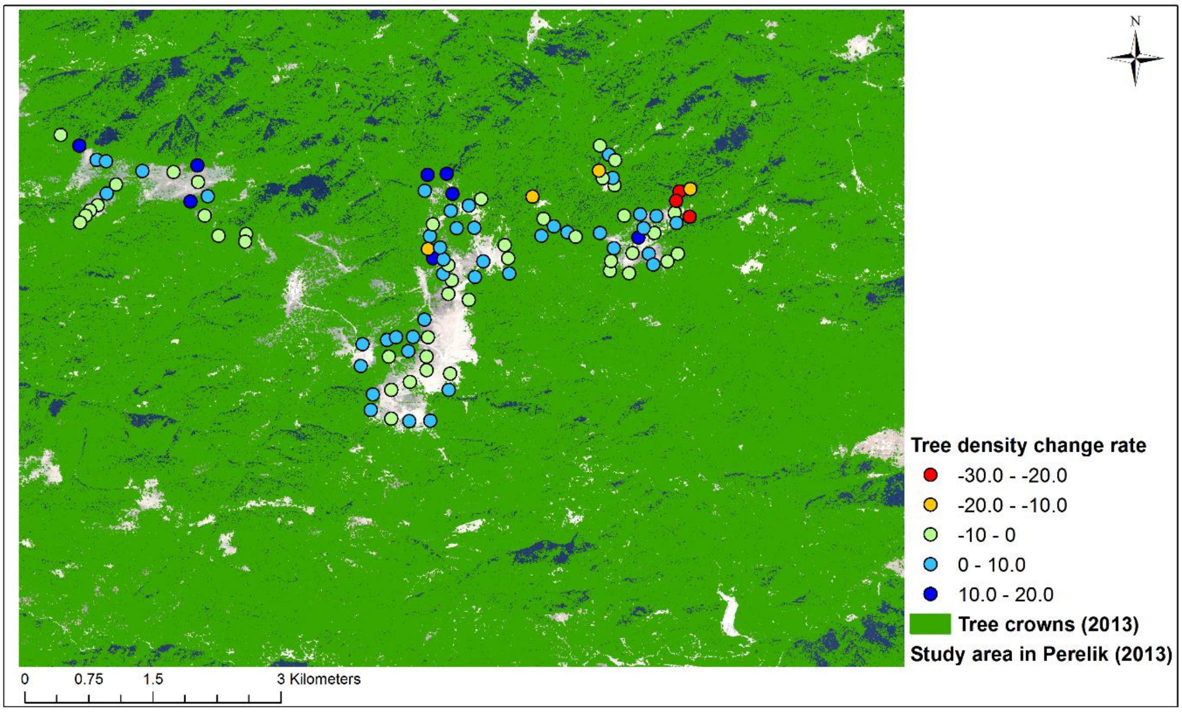



Figure 15 Tree density change rate of each sample plot shown spatially on classification map of 2013


Figure 16 Histograms of canopy change rate (a) and tree density change rate (b) visualizing the frequency distribution

### 3.3. Estimate tree colonization rate

#### 3.3.1. Exploratory data analysis

Figure 17 shows that steepness of slope of sample plots were well distributed from 0 degree to about 38 degree and there were more sample plots with steepness from about 15 degree to 23 degree. Northness was not well distributed as shown in Figure 18. There were more sample plots located on north-facing slopes and south-facing slopes. In Figure 19, it is shown that the grazing classes of sample plots were not well distributed. Sample plots are more located on non-grazing area.

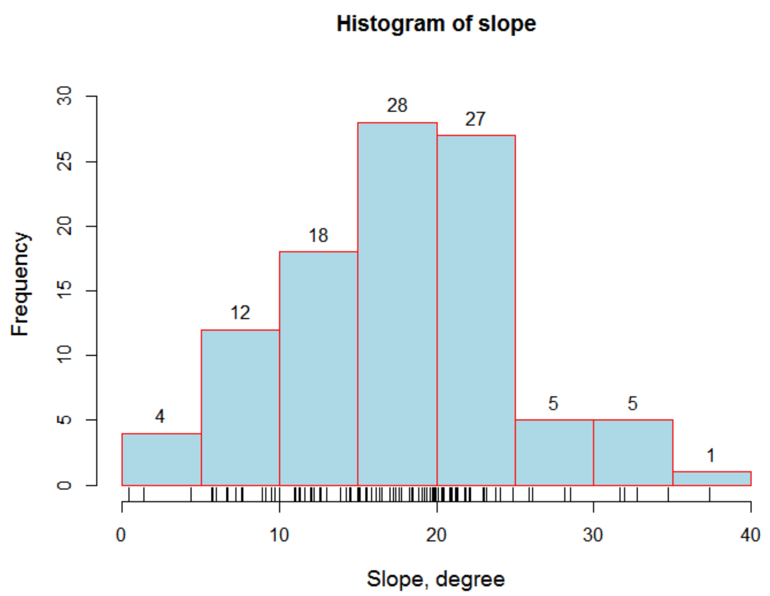



Figure 17 Histogram of steepness of slope visualizing the frequency distribution

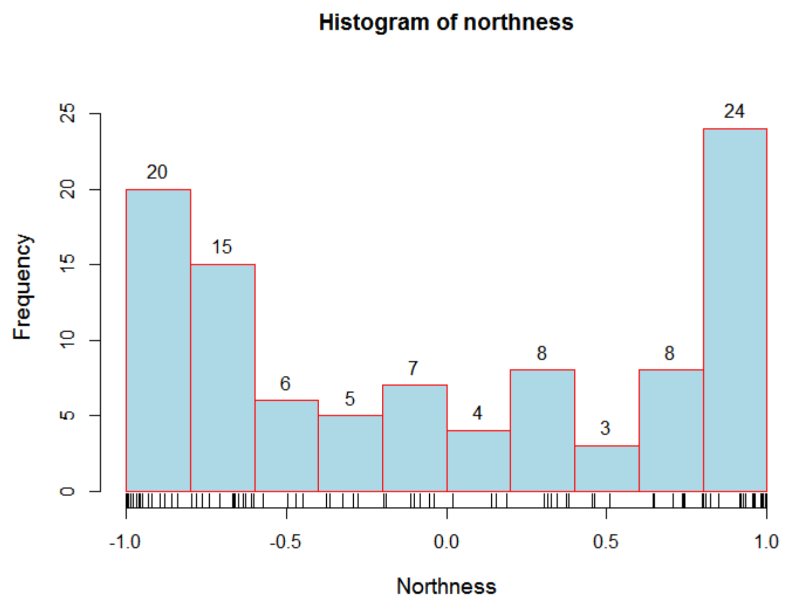



Figure 18 Histogram of northness visualizing the frequency distribution

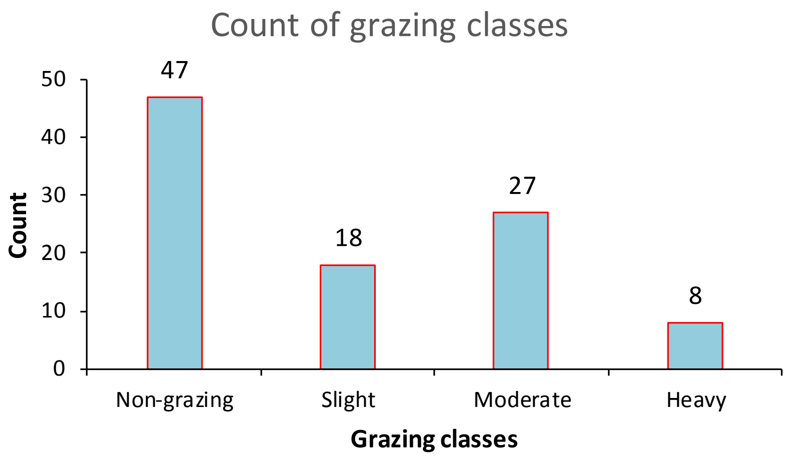



Figure 19 Bar chart of grazing classes visualizing the frequency distribution

### 3.3.2. Relation between colonization time and canopy cover / tree density change rate

From the Table 10 and Figure 20, it can be seen that canopy cover change rate and tree density change rate had significant negative relation with maximum age which means that lower canopy cover change rate/tree density change rate indicated that forest were older. However, low R2 value revealed that maximum age was not accurately predicted by change rate of canopy cover or tree density. Therefore, canopy cover change rate and tree density change rate can be used to indicate the colonization time but with low accuracy.

Table 10 Coefficients, $R^2$ of two linear models

| Models | Canopy cover change-maximum age | Tree density change-maximum age |
|---|---|---|
| P value | $2.878e^{-04}$ *** | $9.849e^{-04}$*** |
| $R^2$ | 0.126 | 0.105 |
| Slope | -14.935 | -1.447 |

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

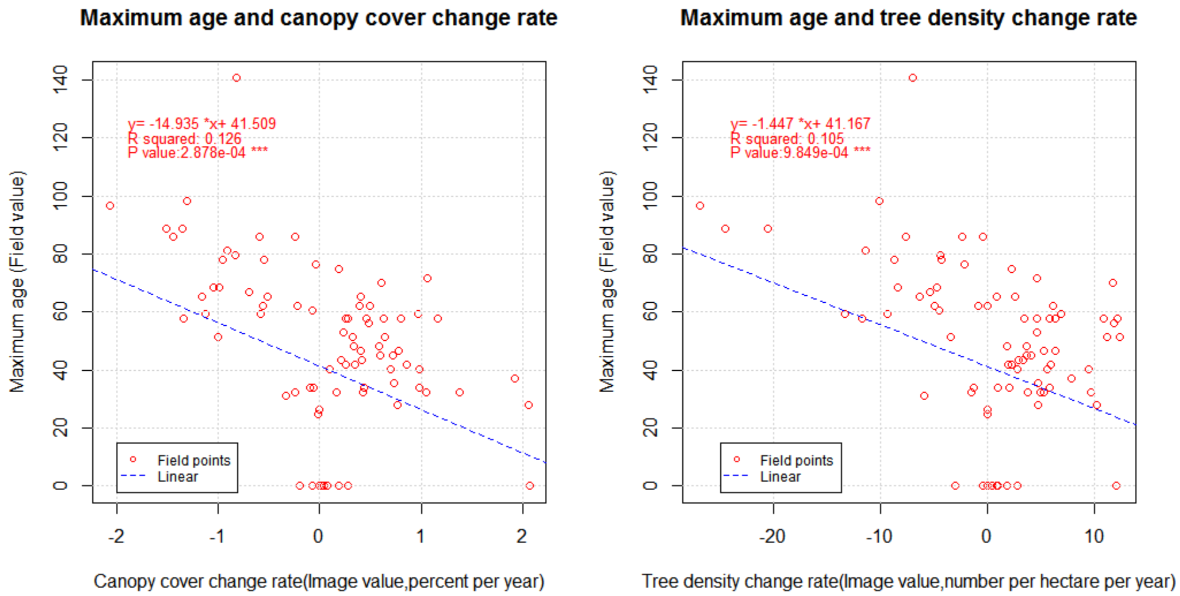



Figure 20 Scatter plot of maximum age-canopy cover change and maximum age-tree density change

## 3.4. Influence of factors on colonization

### 3.4.1. Collinearity

As illustrated in Table 11, Pairwise Pearson's correlation coefficient between steepness of slope and northness as well as VIF of these two continuous variables was calculated. The correlation coefficient is lower than 0.5 which means there is no collinearity between steepness of slope and northness. The VIFs of steepness of slope and northness were both lower than 10 and it indicates that collinearity was not likely to be a problem when modelling.

In Table 12, it can be seen that slope on non-grazing and moderate grazing have significant difference with slope and heavy grazing has significantly different northness from non-grazing.

Table 11 Pairwise Pearson correlation coefficient between steepness of slope and northness and VIF of each variable

| | | Steepness of slope | Northness |
|---|---|---|---|
| Pairwise Pearson correlation coefficient | Steepness of slope | 1.000 | 0.055 |
| | Northness | 0.055 | 1.000 |
| VIF | | 1.093 | 1.006 |

Table 12 P values and $R^2$ of each grazing classes in bivariate linear regressions with steepness of slope or northness

| | Steepness of slope | Northness |
|---|---|---|
| Non grazing | $< 2e^{-16}$ *** | 0.9797 |
| Slight grazing | 0.3339 | 0.7595 |
| Moderate grazing | 0.00511 ** | 0.3209 |
| Heavy grazing | 0.08241 . | 0.0305 * |

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

### 3.4.2. Multivariate linear regression

Surprisingly there are only significant relations between canopy cover change and slight grazing and moderate grazing as shown in Table 13. It can be seen that slight grazing and moderate grazing had positive influence on canopy cover change rate. Besides high P value of the variables, adjusted $R^2$ value are also extremely low in both models.

Table 13 Coefficients, $R^2$ of two multivariate linear models

| Models | | Slope | P value | Adjusted $R^2$ |
|---|---|---|---|---|
| Responsible variables | Explanatory variables | | | |
| Canopy cover change | Steepness of slope | 0.009 | 0.417 | 0.019 |
| | Northness | 0.015 | 0.883 | |
| | Non grazing | -0.299 | 0.201 | |
| | Slight grazing | 0.416 | 0.044 * | |
| | Moderate grazing | 0.395 | 0.035 * | |
| | Heavy grazing | 0.366 | 0.210 | |
| Tree density change | Steepness of slope | -0.015 | 0.882 | -0.011 |
| | Northness | -0.583 | 0.557 | |
| | Non grazing | -0.640 | 0.774 | |
| | Slight grazing | 3.154 | 0.110 | |
| | Moderate grazing | 2.210 | 0.216 | |
| | Heavy grazing | 1.700 | 0.543 | |

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# 4. DISCUSSION

## 4.1. Factors influencing tree colonization

In this study, several hypotheses about how factors influencing tree colonization were put forward and evaluated. However, it was found that terrain has no effect on canopy cover change rate or tree density change rate which were different from the hypotheses given where canopy cover change rate or tree density change rate is higher on south-facing slope and gentler slope. As discussed by Kienast et al (1999), heavy grazing forest is more likely to be open while in this study, only slight grazing and moderate grazing were found to have significant relation with canopy cover change rate and these two classes of grazing had positive influence on canopy cover change rate, which is in contrast to the hypothesis 4 surprisingly.

Poor accuracy of predicted age, canopy cover or tree density may result in these unexpected results. Furthermore, collinearity between grazing and steepness of slope or northness were not confirmed since Pairwise Pearson's correlation coefficient and VIF is not appropriate for categorical variable. New method to detect collinearity between categorical variable and continuous variable should be apply(Giannetti et al., 2014) because if correlation exists in a model, the variance of model will be inflated.

In my opinion, field observations about grazing types may be subjective especially slight grazing and moderate grazing since the observations were only according to grazing evidences (animal steps and animal excreta) from the field.

## 4.2. Tree age-CPA model

It is important to realize that there was no separate Spruce yield table with CPA and tree age available and the data set used for modelling the relation between tree age-CPA was based on the Spruce yield table A which is used for modelling the relation between DBH-CPA. Tree age-DBH was used to convert the DBH into tree age in Spruce yield table A.

In addition, compared to the range of DBH in field observations (2-81 cm) and Spruce yield table A (26-110 cm), the range of the DBH in Spruce yield table B is smaller (12-70 cm). This may lead to error when predict tree age from DBH from field observations or convert DBH into tree age in Spruce yield table A with DBH outside the range of DBH in Spruce yield table B.

## 4.3. Quality of OBIA classified image

OBIA classified images of 2013 and 1965 were evaluated. Accuracy of classified image of 2013 was higher than classified image of 1965. This results from three main cause. Firstly, the maximum age predicted from maximum DBH of each sample plot in field observations was with low accuracy due to model tree age-DBH. The evaluation data for accuracy assessment was based on the predicted maximum age from field observations and thus prediction of maximum age with low accuracy may cause low accuracy in OBIA classified image of 1965. Secondary, although both images have high resolution, image of 2013 is available in RGB (red green blue) color while image of 1965 is only available in panchromatic mode. Juniper, grass and bare land can be more distinguish from trees. Third, the gradually whitened at the edge of image of 1965 made it more difficult to distinguish trees. One of the important criteria in OBIA classification is brightness of object for each class. The gradually whitened image of 1965, however, was necessary to be divided into several parts and also several sets of criteria were needed according to the brightness of trees in each part., which added uncertain to the classification map.

When in dense forest, tree crown and shadow are darker on image while in open area with bare land surrounding, the shadow and tree crown are brighter. Therefore in order to remove the shadow and bare land with the same criteria for the whole image, some tree crowns in dense forest are likely to be assigned as shadow area when removing the shadows in open area; some tree crowns in open area are likely to be assigned as bare land class when removing the bare land area. These two situations will cause the underestimation of tree density in open area and dense forest. There was another situation where a bunch of small trees in dense forest and they were likely to combine as a tree but it was not large enough to divided in to several trees, which will result in overestimated CPA and underestimated tree density.

In addition, Pouliot et al (2002) pointed out that CPA of large tree crowns tend to be underestimated while small tree crown tend to be overestimated but in this study. However, because of tree colonization, small tree crown are more likely to be on open area which increase the possibility to eliminate small trees or overestimate the tree crowns of small trees in open area.

For canopy cover estimated from image, Sample plots in dense forest were underestimated and in wood land sample plots were partially underestimated while in open area sample plots were overestimated. Accuracy of canopy cover in wood land was higher than in dense forest and in open area. These probably resulted from overestimated tree crown and underestimated number of tree crowns in sample plots.

For the purpose of increasing the accuracy of OBIA classification map, it is recommended to use extended spectral ranges for instance red-edge band for vegetation delineating (Schuster, Förster, & Kleinschmit, 2012).

### 4.4. Estimate tree colonization rate and colonization time

In order to indicate colonization time, relation between canopy cover change rate and maximum tree age was modelled as well as relation between tree density change rate and maximum tree age. The models proved that canopy cover change rate/tree density change rate had negative relation with maximum age. Hewitt & Kellman (2004) also concluded that colonization will be facilitate on well-illuminated sites.

Although both relations are significant, canopy cover change rate/tree density change rate only explained small portion of maximum tree age.

# 5. CONCLUSION AND RECOMMENDATION

In this thesis, factors influencing tree colonization were studied.
Canopy cover, tree density, average CPA, maximum DBH and maximum age predicted from image were evaluated with field observation and forestry inventory data. It was found that except average age, the other tree characteristics have significant relation with the actual value.
From the results of evaluation of OBIA classification maps, it can be concluded that canopy cover was less accurate in dense forest. In dense forest canopy cover was underestimated and in open area canopy cover were partially underestimated while in wood land canopy cover were overestimated. Tree density was underestimated for dense forest, wood land and open area while average CPA, maximum DBH and maximum age were mostly overestimated.
Multivariate linear regression was applied between canopy cover change rate/tree density change rate, Terrain (steepness of slope and aspect of slope) and grazing. Canopy cover change rate/tree density change rate was used as dependent variables and terrain and grazing were chosen as explanatory variables.
Surprisingly, it was found that terrain had no significant relation with canopy cover change rate or tree density change rate while only slight grazing and moderate grazing had positive significant relation with canopy cover change rate.
For future study, OBIA is an efficient tool to delineate tree crown from map but it will be more efficient to use extended spectral ranges for instance red-edge band for vegetation delineate. When modelling with mixture of variable for instance, categorical variables and continuous variables, it is worthwhile to find a new solution to detect collinearity in order to confirm collinearity will not be a problem when modelling.

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