DISTRIBUTION MODELLING OF *GLAUCIDIUM PASSERINUM* AND *AEGOLIUS FUNEREUS* USING FOREST STAND STRUCTURE PARAMETERS FROM HIGH RESOLUTION IMAGERY IN RHODOPES MOUNTAINS, BULGARIA

GOLNAZ ASGHARI EZZATI
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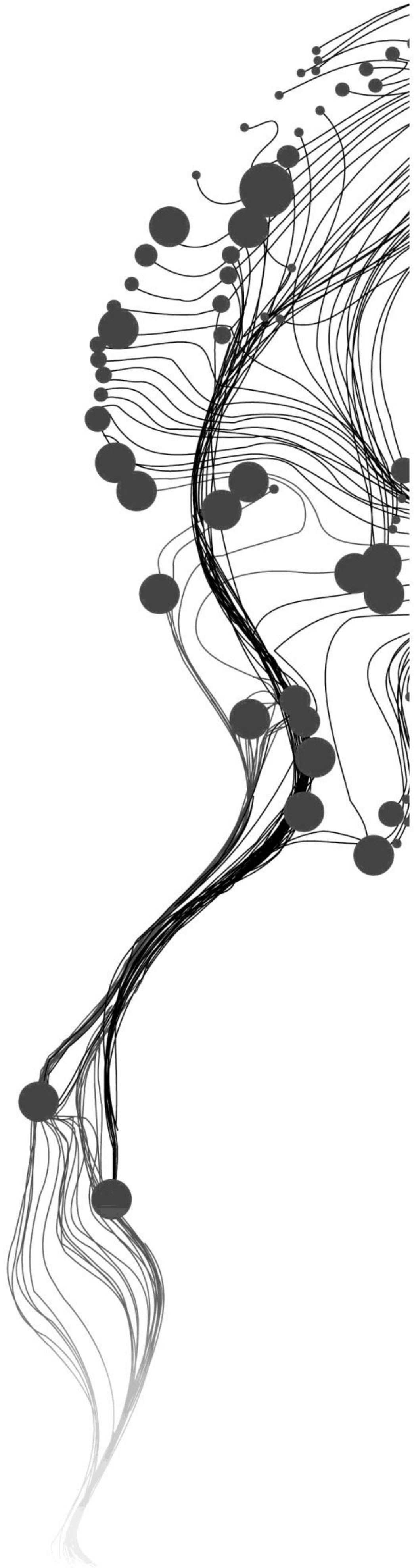
SUPERVISORS:
Dr. Ir. T.A. Groen
Dr. A.G. Toxopeus



Distribution Modelling of *Glaucidium Passerinum* and *Aegolius funereus* using Forest Stand Structure Parameters from High Resolution Imagery in Rhodopes Mountains, Bulgaria

GOLNAZ ASGHARI EZZATI
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Specialization: Natural Resources Management

SUPERVISORS:
Dr. Ir. T.A. Groen
Dr. A.G. Toxopeus

THESIS ASSESSMENT BOARD:
Dr. Y.A. Hussin (Chair)
Prof. Dr. V.G. Jetten (External Examiner, University of Twente)

ABSTRACT

Species distribution modelling (SDM) helps direct biodiversity conservation, monitoring and forest management plans. To target vulnerable areas, modelling distribution of species like owls as apex predators is useful since they are very good indicator of biodiversity and health of the ecosystem. *Glaucidium passerinum* and *Aegolius funereus* are two owl species whose habitat selection behaviour in the old growth forest of Rhodopes Mountains in Bulgaria was studied for this research.

Collecting ground truth data on occurrence points of species is not easy though especially if they inhabit dense forest and rough terrain. Therefore this study tried to use remote sensing techniques to test whether indicators derived from high resolution imagery provide equally significant inputs for distribution models as field based data. Distribution models were generated with topographic variables and image based forest structure parameters and importance of variables in occurrence of either species were compared.
This research also tried to find an appropriate spatial scale of species home range size that explains their distribution best.

The results of generated models could confirm the importance of some previously known predictors in occurrence of both owl species like "Slope". The results also verified preference of *A. funereus* to inhabit trees with larger crown diameters. Moreover the research contributed to existing ecology knowledge of these forest dwelling species in western Rhodope by detecting importance of forest edge to owls presence.
However, the accuracy indicators of generated models were not high enough for the models to be extrapolated. There was also no trend over different home range sizes to indicate which scale can best predict the distribution of either species.

Possible reasons for acquiring models with low accuracy could be due to not including right variables, not having the right range of values for relevant variables, error in data or having generalist species that doesn't respond top strongly to any variables
Thus the usefulness of RS techniques in generating SDMs can not be rejected. Including other predictors like age and DBH of the trees, using LiDAR data to extract tree heights and calibrating the detected individual trees can produce better quality data to improve model accuracy.

Keywords: distribution model, forest stand structure, high resolution imagery, *Glaucidium passerinum, Aegolius funereus*, Rhodopes.

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1. INTRODUCTION

"Species Distribution Modelling" (SDM) is a technique for describing or predicting distribution patterns of species. SDMs, also known as "Ecological Niche Modelling", relate occurrence data of species at known locations with spatial and environmental attributes of those spots (Elith & Leathwick, 2009). This relationship between a species occurrence and elements within the ecosystem it occurs is assumed to be at equilibrium with each other (Elith & Leathwick) and they play significant role in directing biodiversity conservation (Liu, White, & Newell, 2011) and forest management planning (Redon & Luque, 2010). Detecting changes in conditions of one or more controlling factors also indicates changes in distribution of a specific species. Predictive modelling helps quantify the relation between such conditions to assess the impact of changes on species distribution. This helps to create sustainable resource management policies for that species (Yost, Peterson, Gregg, & Miller, 2008).

According to Romulo (2012), there are species whose presence are very good indicator of biodiversity and health of the ecosystem. Therefore studying their distribution pattern is useful for pointing out conservation targets and vulnerable areas. Owls for instance are apex predators which can help in achieving conservation goals at broader ecosystem levels (Romulo). Cholewiak (2003) said 95% of the owls are forest dwelling species who rely on services that the forest offers. Defining the important forest stand structure parameters that indicate the proper conditions in explaining owl occurrence helps generating accordingly monitoring and managing plans. Yet accessing the exact occurrence points and collecting all possibly related ground truth data to their presence is challenging and sometimes not practicable as they might inhabit in remote areas with tough terrains. Advances in remote sensing technology might be useful in overcoming this difficulty and also improve species richness or performance of SDMs (Cord et al., 2014). For owl species like *Glaucidium Passerinum* and *Aegolius funereus* who specially occur at higher altitudes and lands with high degree of slope values, employing remote sensing to detect proxies of forest stand structure parameters might be very helpful in modelling their habitat selection behaviour. These two owl species are two protected species considered to be rare breeding in Bulgaria (Shurulinkov & Stoyanov, 2005, 2006). There are many studies that examined correlation of their occurrence with selected environmental variables based on extensive field surveys, however, the results were rather inconsistent so it is not entirely clear what precisely determines owl's distribution. Moreover, no study has evaluated the potential of using high resolution imagery for modelling their distribution.

The benefit of using high resolution imagery in forestry research is in detecting trees by delineating the crown of individual trees. These delineations can be used to derive important tree and forest characteristics. Ground based measurement of tree crown width is more difficult and time consuming than other forest stand structure parameters (Sönmez, 2009). Although it is still not entirely clear what factors determines these two owl species distribution, it has been claimed that occurrence of them is highly correlated to tree characteristics like tree-cover, diameter at breast height and crown width. Thus employing remote sensing (RS) techniques to extract derivations of these predictors would save time and cost.

Also, a successful development of spatial knowledge of habitat suitabilities of indicator species like owls would assist producing conservation management plans for other cavity-nesting species with similar habitat requirements (Redon & Luque, 2010).

Rhodopes (Rhodopi) Mountains with its extensive old-growth forest in central south Bulgaria looks to be a suitable location to study behaviour of rare breeding bird species as it is claimed to have the richest biodiversity among all mountains of Bulgaria and perhaps even in whole Europe (Terry, Ullrich, & Riecken, 2006). This mountain range is among most valuable areas at the level of the European Union for *Glaucidium passerinum* (*G. passerinum*) and *Aegolius funereus* (*A. funereus*) (Kostadinova & Gramatikov, 2007). It is known to be habitat of largest number of *G. passerinum* in the entire Balkan Peninsula (Shurulinkov, Ralev, Daskalova, & Chakarov, 2007). According to Shurulinkov, Stoyanov, Komitov, Daskalova, and Ralev (2012) the recorded number of *G. passerinum* territories was higher than of *A. funereus* in Rhodopes Mountains. Besides that, Rhodope forest is an old growth forest with a great number of large trees and standing dead trees. According to Angelstam, Bütler, Lazdinis, Mikusinski, and Roberge (2003), dying or dead trees are very important habitat for many plant species and animals as well as known to be best for forestry practices. *G. passerinum* also nest in woodpeckers' holes on very old trees. Thus monitoring and modelling their niche selection helps in understanding status of the forest resources.

Based on many bird fauna studies that have been carried out for decades in Bulgaria, there were some geographically overlapping and also non-overlapping presence points of each species which indicate there could be subtle yet principal differences between their habitat selection behaviour. These differences affect their co existence. Recent studies provide more occurrence data and identified habitat requirements of both species based on vegetation types and characteristics (Ström & Sonerud, 2001; Shurulinkov et al., 2012; Henrioux, Henrioux, Walder, & Chopard, 2003), food availability (Deshler & Murphy, 2012; Zarybnicka, 2009; Suhonen, Halonen, Mappes, & Korpimäki., 2007), hunting strategies (Suhonen et al.; Ström & Sonerud), breeding success (Deshler & Murphy; Pacenovsky & Sotnar, 2010), geological features (Rajković, Grujic, Novic, & Miric, 2013), human interventions (Deshler & Murphy; Flesch & Steidl, 2007) and climatic variables (Catro, Munoz, & Real, 2008). They all tried to focus and measure certain explanatory variables effecting habitat selection of each species independently. The analyses were based on literature, expert knowledge or logical assumptions and estimations.

Though what still needs to be clarified are the main contributors to occurrence of overlapping presence points and comparison between similarity and differences of their habitat requirements. The focus of this study is to test whether such environmental variables including forest parameters can be derived from remote sensing techniques to define their suitable habitat. According to previous studies it looks like there are probably three main factors which explain differences, competition on food (Suhonen et al., 2007; Andrle, 2011), different timing of activity (Pacenovsky & Shurulinkov, 2008) and surviving in a predator-prey community.

Meanwhile it is also known that the biggest threat to both species is human interventions, mainly intensive forestry activities and development of tourism attractions (Shurulinkov et al., 2007). Conservation management plans at local scale like Rhodopes Mountains need fine-scale data, and such studies require continues maps of environmental variables. So the challenge is to generate a model from small scale aerial image to be accurate enough to be extrapolated.

To generate accurate models it is important to drive variables at a correct spatial scale. Modelling species distribution over very large areas will not say much about suitability but at very small extents would neither. So establishing the right home range size is a useful study to improve the modelling results for these species. Therefore the current study also tries to find the home range size that explains their territory best. To answer this question, the mean territory size of *A. funereus* as the larger owl species was estimated from previous studies. There were inconsistency and controversial records in defining the best home range for *A. funereus*. Kouba, Bartos, and Stastny (2013) considered a home range between 30-57 hectare suitable for nesting and foraging depending on prey abundance. But Santangeli, Hakkarainen, and

Korpirmaki (2012) found a home range between 40-293 hectare, where "spruce" forest was the best forest type predictor but food availability didn't change the territory size which is in contrast with Kouba et al. findings. Although they claimed that in a dense forest, increasing the cover decrease the home range size of this species (Santangeli et al.). From many papers and previous investigations, an average territory size of 100 hectare was considered most appropriate for *A. funereus*. Rajkovic et al. (2013) suggested a roughly estimation of one territory in 100 hectare. Also Jedrzejewska and Jedrzejewski (1998) estimated their home range to be around 1.1 km^2.

As mentioned earlier, Rhodopes forest is very old and dense, and the dominant tree species in the study area was "spruce" which is known to provide a suitable habitat for both *G. passerinum* and *A. funereus*. So it is a very good example of a forest where the tree cover is dominated by a single tree species and where these bird species occur. To examine the impact of such forest structure on the territory size, the accuracy of SDMs based on average stand characteristics measured at three different home range sizes were investigated. The selected home range sizes to be evaluated were 100, 50 and 25 hectare.

To perform image processing operations in this study, eCognition Developer 64 and ArcMap 10.2.1 were used. eCognition Developer employs Object Based Image Analyses (OBIA) technique to interprets the image by certain characteristics like their smoothness, shape, size or spatial arrangement of certain features (Lang, Albrecht, & Blaschke, 2006.). OBIA has the ability to use spatial information implicit within remote sensing which is often neglected (Hay & Castilla, 2006). This makes it useful in studying forest-characteristics which are not homogenous on a high resolution imagery that contains high level of details.

1.1. Rhodopes Mountains

The Rhodopes Mountains form the most extensive mountain range in Bulgaria and cover nearly one seventh of the whole country ("Rhodope Mountains", 2014). About 80 percent of the region is in Bulgaria and the southernmost of it is situated in Greece. Geomorphologically, it is the oldest mountain range in Bulgaria with a complex system of very old forest, ridges with various height and width, river valleys and ravines. Such environmental conditions provide excellent opportunity for unique biodiversity in this vast area (Greek biotope/wetland centre, 2008).

The great variety in vegetation, climate and terrain provides suitable habitat for over 300 species of bird (Wild Rodopi NGO, 2012). Among them, there are 36 birds of prey which inhabit Rhodopes making it an important habitat in Europe for many threatened species (Sierdsema, Ploeg, Jansen, & Jansen, 2010).

Figure 1. Rhodopes Forest in Western Rhodopes Mountain, Bulgaria.

1.2. Owl Species

1.2.1. Glaucidium passerinum

Glaucidium passerinum, also known as Euroasian Pygmy owls are the sole member of the widespread genus *Glaucidium* in Europe. They are diurnal owls [owls that hunt during daylight] (Härmä et al., 2011), glacial relict species [species remained from last glacial period], not shy of human and known to be the smallest owl in Europe (Lewis, 2013).

This species was considered extinct in Bulgaria until recently (Shurulinkov & Stoyanov, 2006). Therefore there are still few published documents on their presence in different part of the country.
On a national level their population is estimated to reach between 240-290 breeding pairs (Shurulinkov et al., 2007). Several studies have estimated the number of *G. passerinum* in Rhodopes Mountains to vary between 120-200 (Pacenovsly & Shurulinkov, 2008; Shurulinkov et al., 2012).

Figure 2. *Glaucidium Passerinum* (Breider, 2011)

1.2.2. Aegolius funereus

Aegolius funereus also knows as Boreal owl or Tengmalm's owl after Swedish naturalist Peter Gustaf Tengmalm ("Boreal owl", 2014) are nocturnal small owls, they avoid humans and they have a broad habitat ranging from the mountains in Alaska, Canada and America to northern Europe and Asia (Owl Research Institutes, 2013).

These species are mostly found in Scandinavia but also live in subalpine regions and forests in the northern hemisphere and central mountain regions (Hayward & Hayward, 1991; Lewis, 2013).
Published data on occurrence of *A. funereus* in Bulgaria goes back to late 1960s (Shurulinkov, 2012) though there is evidence to claim they were widely distributed in mountains mainly in Rhodopes at the beginning of 20th century. Their total population is estimated to vary between 1025-1400 pairs in the whole country (Shurulinkov & Stonyanov, 2005).

Figure 3. *Aegolius funereus* (Falsterbo, 2008)

1.2.3. Similarities, Differences and Threats

The greatest similarity between these two species is that they are highly dependent on forest maturity (Ström & Sonerud, 2001) and they have similar hunting strategy as they are both "forest dwelling sit- and-wait predators" (Härmä et al., 2011, p 91). Yet due to the slightly larger size of *A. funereus* and their bilateral ear asymmetry (Ström & Sonerud) that enables directional hearing in total darkness, it is easier for them to find and catch preys.

Suhonen et al. (2007) also studied the effect of predatory interactions between the two on larder size as a function of distance and diameter of nest-boxes entrance. They have concluded that *G. passerinum* can co-exist with the latter but due to competition for food resources that are only available during late autumn and winter time each year (Suhonen, 1993), their hunting success is lower resulting in smaller larder size in presence of *A. funereus*.
In a comprehensive literature review on diet selection of a number of raptor species in northern Europe by Andrle (2011), it was reported that one third of the total diet of *G. passerinum* is composed of birds whereas this number was only 3.6% for *A. funereus* (Andrle). On the other hand more than 90 % of the *A. funereus* diet has been recorded to be mammals as with *G. passerinum* it was 65 percent (Lewis, 2013; Andrle).

It can be suggested that occurrence of *G. passerinum* in non-overlapping areas might be explained by their tendency to spatially avoid (Suhonen et al., 2007) other birds of prey including *A. funereus* and inhabit areas where climate condition is not suitable for their competitors. Risk of predation by other larger birds of prey is the natural threat *to G. passerinum*. But in broader scale *A. funereus* are not endangered and are rarely threatened by human hunting.
Yet both *G. passerinum* and *A. funereus* have been threatened by large scale legal and illegal logging during previous years. The consequence is that old coniferous forests are disappearing and this affects mostly *A. funereus*. In a study in Finland decreasing rate of this species was estimated by 2% each year ("Tengmalm's Owl- Aegolius funereus", 2014).

On the other hand, *G. passerinum* can adapt itself better to forestry activities and their presence was recorded in areas where sustainable forestry was practiced, though still the biggest threat in Rhodopes Mountains is habitat fragmentation. Shurulinkov et al. (2007) claimed that clearing trees in the upper river catchment has also destroyed their best habitats apart from erosion and creating higher risk of flooding in the downstream. In the same study they claimed the density of this species was higher in closed forests with no forestry activities compared to sites where many logging activities were illegally practiced (Shurulinkov et al.).

1.2.4. Assumptions

There are other ecological factors that can affect the occurrence of both species. So according to available time and data, three main assumptions were made that might have introduced some bias into the study.
1- Presence points of both species represent their presence regardless of nesting, roosting or foraging.
2- It is assumed that competition for food does not affect the reproductive success of *G. passerinum* owls as there are no evidence yet which supports such hypothesis (Suhonen et al., 2007).
3- *G. passerinum* is under risk of predation by other larger birds of prey mainly *Strix aluco* known as Euroasian Tawny owl. This owl is widely distributed through whole Europe and also in Bulgaria. It is even believed that increasing population of *Strix aluco* resulted in disappearing of *G. passerinum* from parts of Germany (Lewis, 2013). But this research is excluding risk of becoming prey to other animals as there is no data available on their density and distribution.

1.3. Most Important Explanatory Variables

Among the environmental factors defined by literature to contribute to *G. passerinum* and *A. funereus* occurrence in different places in the world, there are environmental conditions that are repeatedly reported in various papers and surveys. The most important habitat requirements are discussed briefly in this section.

1.3.1. Forest type

There are many similarities between types of forest preferred by *G. passerinum* and *A. funereus*. They both nest in mature coniferous forests in different combination of tree species.
The most important tree species that provide suitable habitat for *G. Passerinum* and *A. funereus* to nest and forage are old forests of Spruce, Scots Pine, European Beech and European silver Fir. (Shurulinkov et al., 2012; Romulo, 2012; Shurulinkov, 2005; Cote, Doyon & Bergeron, 2004; Ström & Sonerud, 2001; Shurulinkov & Stonayov, 2006; Korpimäki, 1981).

Comparing *G. passerinum* with *A. funereus*, Redon & Luque (2010) suggested that the first depends more on presence of Norway Spruce and the latter on European Beech.

1.3.2. Altitude

The recorded altitudes of both species occurrence from many studies suggested their tendency to inhabit h igher elevation. Gattermayr et al. (2013) has called *G. passerinum* "birds of higher altitude". This speciessee ms to be quite dependant to altitudes for choosing suitable habitat as they show consistent reliability to hig her altitudes starting from 1400m up to 1930m above sea level (Shurulinkov et al., 2005, 2007).

However the records on elevation values were not consistent for *A. funereus*. Their occurrence has been recorded in elevation ranging as low as 790 meter (Rajkovic et al., 2013) up to 1800 meter above sea level (Shurulinkov et al., 2012; Shurulinkov & Stoyanov, 2006, 2005; Rajkovic et al.) in different places.
This inconsistency in results might be due to the fact that environmental conditions change when these species move north or south. So they seem to be more flexible to altitude variation as long as other favourable conditions are provided.

1.3.3. Aspect, Slope and Daylight Period for Hunting

There were some studies claiming that topography is highly correlated to distribution pattern of both species and slope appears to contribute significantly to their occurrence (Redon & Luque, 2010; Shurulinkov et al., 2006; Cichocki, Slizowski, & Bochenski, 2004). Yet again records on correlation between their occurrence and slope were not consistent and their presence was recorded in not too steep slopes of less than 35° (Gattermayr et al. ,2013).

The importance of aspect for *A. funereus* is explained by the fact that they are nocturnal owls who are active in twilight. Zarybnicka (2009) suggested that male of *A. funereus* starts hunting after the sunset with two peaks at late dust (20:00-22:00) and early dawn (2:00-5:00). She suggested that their activity declines significantly between sunrise and sunset and light condition limits their hunting Thus it can be hypothesized that their habitat is correlated to west facing slopes. These slopes provide longer twilight time since compared to east facing slope, it is exposed to sun at an earlier time of the day.
Western slopes also provide *A. funereus* with cooler climatic conditions to avoid summer heat (Hayward et al., 1993). At high elevation, the surface facing sun warms dramatically on a clear day (Price et al, 2013), and this can cause too hot conditions for this species.

It has also been shown that larger owl species like *Strix aluco* which prey on *G. passerinum* and A. *funereus,* prefer lower elevation and slopes facing the sun (Rajkovic et al., 2013). Thus the importance of westness might also be in avoiding predation by other birds of prey.
Unlike *A. funereus*, the presence of *G. passerinum* has been recorded during day light as they lack the ability to hunt in total darkness. Thus it seems like being more exposed to light would suit them since it provides them longer hunting period.

So studying the contribution of topographic variables in occurrence of each species in overlapping and non-overlapping presence points would probably provide more insight into their habitat selection behaviour.

1.3.4. Tree Diameter at Breast Height

Several studies came with a lower threshold for tree DBH above which trees would be suitable to offer nesting locations for *A. funereus* ranging between 30 and 38 cm (Cote et al., 2004; Hayward, 1993; Heinrish et al., 1999)
The required DBH for *G. passerinum* habitat which is addressed in fewer cases was reported to be about 45 ± 9 centimetres by Ministry of Water, Land and Air protection (2004).

DBH is also a proxy of age of trees and growing condition. Both of these species inhabit trees around 80 years old or older (Shurulinkov et al., 2007, 2012; Cote et al., 2004) since they both nest in cavity holes made by woodpeckers on very old or dying trees.

Therefore it can be suggested from previous studies that DBH plays significant role in defining suitable nesting locations of both species but what is lacking in literature is possible correlation of variation of DBH and average DBH with distribution pattern of owls. Since it was not possible to derive DBH directly from an aerial image, the correlation between variations of tree crown values was studied in this research.

1.3.5. Cover Requirements/ Canopy Closure

The presence of the *A. funereus* is generally associated with dense coniferous forests (Johnsgard, 1988). What was common in different observations was the importance of cover of old forest in increasing survival (Hakkarainen et al., 2008). But habitat cover requirements seem to differ between summer and winter times (Hayward et al., 1993). As a cold-adapted species they select dense and shaded sites with lower temperature for roosting during summer time while less specific roosting site selection seems to occur during winter (Hayward et al.). Several studies reported their favourable habitats to be stands with multi-layered canopy which is close enough to provide shelter, and understory which is open enough to provide food in mountainous areas (Hayward et al.; Whitman, 2001; Cote et al., 2004).

Yet there is a threshold on how open the terrestrial habitat should be since foraging habitat value in complete openings reduced according to distance to forest edge (Cote et al., 2004). The explanation for this behaviour could be *A. funereus*‘ reluctance to cross large open areas (Cote et al.) because they try to avoid exposing themselves to other larger and stronger birds of prey. And if the canopy closure is too dense, no suitable ground layer and good cover of herb will develop (Guenette & Villard, 2005).

As for *G. passerinum*, Deutschmann (2013) said they would have food supply year-round if they are in a light canopy closure of old stock combined with an open forest structure since diverse herb layers protect their basic food meaning small mammals and birds. Gattermayr et al. (2013) reported a medium canopy cover in their habitat.

1.3.6. Distance to Forest Edge

The forest edge is a transition from forest to another habitat. Plants that grow in the edge are different or if they also grow in middle of the forest, they look different since they are more exposed to sun light which changes the vegetation structure (McCollin, 2006). For instance shrubs are bushier and more abundant in the edge than in the middle of the forest and this provides good habitat for voles (Barrett &

Peles, 1999) which are an important part of owls' diet.

But there is much confusion on the impact of distance to forest edge in selecting suitable habitat for nesting and foraging of both species. Some older studies supported the hypothesis that *A. funereus* benefit from clear-cuts because they can hunt on voles easier (Hakkarainen et al., 1996). On the other hand many other reports argued that forestry activities have serious negative effect on their habitat selection (Shurulinkov et al., 2012; Zarybnicka, 2009). Also it is believed that the human-avoidance nature of this species is another reason why they are reluctant to be close to forest edge.

On the contrary, *G. passerinum* are more tolerant to forestry activities and their presence was recorded in interspersed open areas, positively associated with clear cutting (Gattermayr, 2013). According to Deutschmann (2013) they only avoided vast clear-cuts. The tendency of being close to forest-edge could be explained by availability of a higher density of field voles (Hakkarainen et al., 1996) and high quality of such habitats in less woody areas (Hayward et al., 1993). Flesch & Steidl (2007) supported the importance of distance to vegetation edge too, suggesting that such margins increase access and visibility over preys.

For clarifying the real effect of distance to forest edge on habitat selection, a hypothesis was made assuming *G. passerinum* occurrence has strong negative correlation to distance to forest margin as for *A. funereus* it would be positive. Though what the optimum threshold and gradient could be is still unclear and needs more investigation.

1.4. Research problem

Until 20 years ago it was believed that *G. passerinum* in Bulgaria was extinct but more data on occurrence of this endangered species, as well as on *A. funereus,* has been recorded in different mountain ranges during previous years (Shurulinkov & Stoyanov, 2005). The records show there are areas inhabited by both species as well as quite distinct areas inhabited by only one. Extensive field surveys tried to define their habitat selection behaviour based on different stand structure and landform features but there are inconsistency and contradictions in the results of these studies. This hampers the evaluation of the contribution of different variables in explaining the overlap and non-overlap of their home ranges

So far no studies have modelled their presence with all possible explanatory variables to analyse the importance of environmental factors. It is also not known yet how significant variables contribute to explain differences in overlap between these two species. The estimation of their best home range size is also not constant in different studies. This might be due to the tough terrain of the suitable habitat of these species which makes it difficult to reach their exact point of occurrence and collect all possible explanatory variables in a well representative area of their territory.

Until recently, the most popular and accurate method in modelling species distribution have been relating their occurrence to actual ground measurement of possible predictors. But according to Tzvetan Zlatanov (personal communication, September 2014) from Forest Research Institute of Sofia, accuracy of distribution models of these two owl species with selected ground truth data was not satisfactory. Still, no topographic variables or distance to forest margins were introduced to their model. Besides, the question arose about the appropriate home range size that would explain their nesting habitat better.

Thus the current study intended to model the distribution patterns of *A. funereus* and *G. passerinum* by producing environmental data from remote sensing information. If such models are accurate enough, they can be extrapolated to other areas, overcoming limitations of time, budget and challenging terrain.

1.5. Research Objectives

This research aims to develop models explaining the distribution of *G. passerinum* and *A. funereus* from forest stand structure parameters and topographic variables in Rhodopes Mountains that are derived from high resolution imagery. Additionally, model accuracy while considering different territory sizes will be studied.

1.5.1. General Objectives

The general objective of this study is to explain differences in habitat selection of *G. passerinum* and *A. Funereus* in Rhodopes Mountain by identifying the most important explanatory variables in defining their habitat selection behaviour.

1.5.2. Specific Objectives

1. Identify differences in importance of topographic variables in defining habitat requirements of *G. passerinum* and *A. funereus* from geographically overlapping and non-overlapping presence points.
2. Generate distribution model from proxies of stand structure parameters derived from high resolution imagery.
3. Find home range size of each species that explains their distribution best.

1.6. Research Questions

1. What are the differences between importance of topographic variables in generating distribution models of *G. passerinum* and *A. funereus*?
2. Which of explanatory variables are most important in defining the occurrence of *G. passerinum* and *A. funereus*?
3. Can image based forest structure indicators provide equally-significant input for distribution models as field based data can?
4. Do models become more accurate when forest stand structure parameters based on larger extents are considered as explanatory variables?

1.7. Hypothesis

Hypothesis 1: Testing the concept that topographic variables explain habitat selection behaviour.

1.1. H1. There is a significant positive correlation between western aspect and occurrence of *A. funereus* since western aspect provides longer twilight period for hunting.
1.2. H1. Altitude is a significant explanatory variable in defining suitable habitat for *G. passerinum* because it enables them to look for preys in a larger ground area and provides safe nesting site to avoid risk from hunting by other birds of prey.

Hypothesis 2: Testing the concept that by employing remote sensing techniques, proxies of forest stand structure parameters can be extracted from high resolution imagery to fit distribution models with high level of accuracy.

2.1. H1. The accuracy of distribution models based on image derived proxies is equally reliable as models generated by ground based measurements so the models can be extrapolated to other areas.

2.2. H1. Probability of occurrence of both species is higher with larger tree crowns (as a representative of diameter at breast height) while occurrence of *A. funereus* has greater probability with larger crown diameter classes than *G. passerinum* who prefer to nest on younger trees where small birds as preys are numerous.
2.3. H1. There is a strong correlation between "Forest Edge"-related variables and occurrence of both species as density of small mammals and passerine prey is higher in the margins.

Hypothesis 3: Testing the concept that deriving forest stand structure parameters from larger extent of home range size could increase the accuracy of the model.

3. H1. Models become more accurate when forest stand structure parameters as explanatory variables are derived from a larger extent of home range size.

2. MATERIALS AND METHODS

The approach toward meeting the objectives of this research was carried out in two main steps; image processing to extract information from high resolution imagery, and statistical analyses to model species habitat selection behaviour. Each step is explained in details in this chapter.
The data was taken from three sources; secondary data of presence/absence points of both owl species, extracted geological features from Digital Elevation Model, and information extracted from high resolution aerial photography of the study area.

2.1. Actual Data

2.1.1. Aerial Imagery of the Study Area

The study area of this research is located in south Bulgaria, in the centre of Rhodopes Mountains and it extends approximately from 24.514000-24.658000 longitude and 41.600000- 41.740000 latitude. It covers an area of about 174 square kilometres.
The high resolution aerial image used in this study was produced by georeferencing aerial images from Google-earth using 421 ground control points to cover the study area. These images were from October 2013 provided by CNES/Astrium satellite with pixel size of 0.5 * 0.7.

Figure 4. Map of Bulgaria with Georeferenced image of high resolution satellite imagery of the study area from Google- Earth.

2.1.2. Presence/ Absence Data of *A. funereus* and *G. passerinum*

A database of presence/absence points of both species was provided by the Forest Research Institute of Sofia thanks to Boris Nikolov and Iva Hristova-Nikolova. The fieldwork was conducted in autumn 2012, with two field visits on 8-14 September and 24 September– 1 October. Autumn was chosen an appropriate time to conduct the bird survey since in spring time the steep terrain of coniferous belt in high mountains of central Europe is covered with lots of snow which makes it hardly accessible. Besides, the weather condition is not good enough to conduct a field work for a long time. The vocal activity of owls is also well expressed similar to the springtime and their territories appear to be the same as well.

The total length of the surveyed transects was 49.9 km on altitude higher than 1450 meter. The distance between locations (points) were set at 500- 700 meters depending on the local terrain. Presence of the species was probed by imitating their call, in order to entice the species to respond. These imitation sessions for each point lasted 13 minutes with first three minutes of no sound provocation. The next ten minutes were split equally between both species to provoke owls by imitating their advertising call. The owl survey started at dusk in the evening about sunset (19:30h; GMT+3) and lasted for three hours. Daytime transects started at about 4:30h (GMT+3) until some time after sunrise at about 7:30h.
This data set represents 49 presence points of *A. funereus*, 11 presence points of *G. passerinum* and 12 geographically overlapping presence points of both species. Also 53 true absence points were recorded. The coordinates of these points was accompanied by approximate mean elevation in meter close to actual points of presence/absence.

Additionally, eight presence points were added by georeferencing two distribution maps from "Digital Version of Red Data Book of Bulgaria" published by the Institute of Zoology (2011), and a project report published by Shurulinkov et al. (2012).
Two out of these eight points were added as occurrence points of *G. passerinum* from "The Red Data Book". And the other six points were added from the published results (maps) of birds' survey conducted by Shurulinkov et al. (2012). Their findings added three presence points to each species. Their owl search was carried out during autumn and spring when the weather condition was favourable and during day and night. The localities of *A. funereus* were recorded only during dusk, down and night time whereas daytime transects for *G. passerinum* showed good results.
The georeferenced maps were then digitized to make a Point shapefile on occurrence points of owls. Then it was clipped to the extent of the study area.

2.1.3. Digital Elevation Model

Digital Elevation Model used for this study was based on the ASTER GDEM image downloaded from the internet (http://asterweb.jpl.nasa.gov/gdem.asp.The ASTER GDEM has a ground resolution of approximately 30 meter and the accuracy is estimated to be 20 meter vertically and 30 horizontally meter at 95% confidence .From this map, aspect, altitude and slope were extracted.

2.2. Exploring and Examining the Secondary Data

Presence and absence points were displayed in same coordinate system to check possible overlap and duplicate records.

The field recorded elevation at occurrence points and DEM based elevations were compared by a boxplot (Figure 5) and histogram (Figure 6). The DEM was covering a wider range of altitude and it represented continues data with no gaps between records. It was also mentioned by Tzvetan Zlatanov from Forest Research Institute of Sofia through personal communication that recorded elevation values might not be precise and accurate enough to be used in modelling. Therefore elevation values extracted from DEM were assumed to be more accurate for fitting the model.

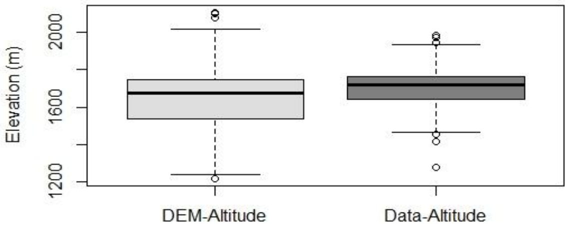

Figure 5. Boxplot of Altitude values extracted from DEM (left) and Altitude values from secondary data (right)

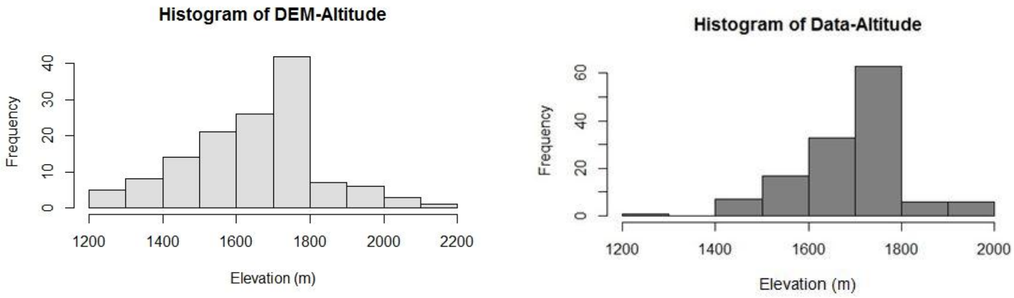

Figure 6. Histogram representing distribution of Altitude values extracted from DEM (left) and Altitude from secondary data (right)

2.2.1. Transforming Aspect to Westness

Aspect needed to be converted into westness (0 pointing east and 180 pointing west) for the hypothesis on westness. This was done using "Folded aspect" (Equation 1) (Muthoni, 2010) to rescale 0-360 degree to 0-180 where 0 corresponds to East and 180 to west (McCune & Keon, 2002).

$$\text{Westness} = |(180-|(\text{Aspect}-270)|)| \qquad \text{Equation 1}$$

2.3. Image Processing and Distribution Modelling Workflow

Figure 7 on the following page illustrates the general approach to modelling distribution of owl species with three datasets of occurrence points, Digital Elevation Map and high resolution aerial imagery of the study area.

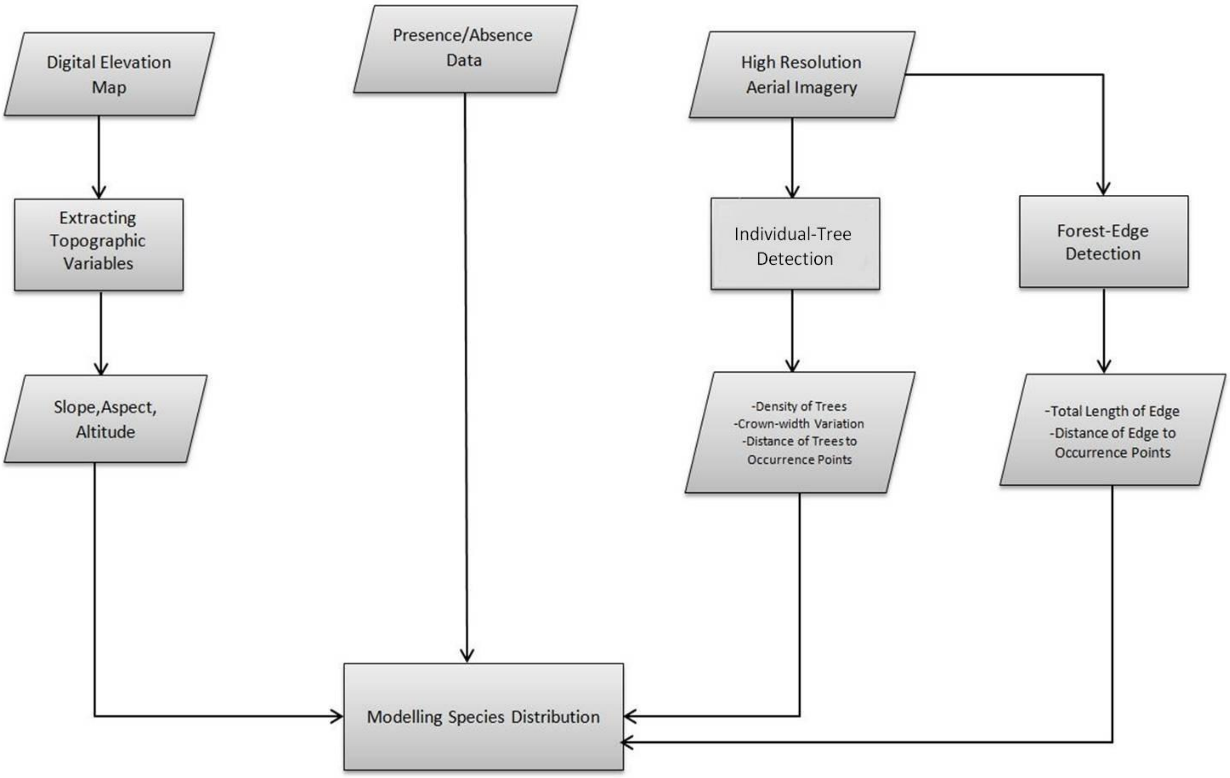

Figure 7. General approach to modelling species distribution from high resolution imagery data.

2.4. Image Processing: Deriving Proxies of Stand Structure Parameters from High Resolution Satellite Imagery

To extract proxies of forest stand structure parameters the image was processed in several steps. The final results that were used in statistical analyses were total number of delineated single trees (from detecting crown projection area) based on variation in crown width, and length of forest edge detected from high resolution aerial imagery. Before images were processed, to save on processing time, the images were masked for the locations for which presence and absence data was available. This reduced the total extent that needed to be processed considerably. The masking was based on a buffer of 570 m around each presence and absence point in the study area.

2.4.1. Single Tree Crown Detection

The georeferenced high resolution images from Google-Earth were in RGB band so the only tree parameter detectable was individual tree crowns. Tree crown detection was performed by employing e-Cognition Developer 64 and ArcMap 10.2.1 software to identify the individual crowns of trees. These crowns are indicated as separate polygons, and from these polygons, the crown projection area (CPA) can be derived. Also, the number of trees can be calculated. This procedure involves three main steps. First the class of “Forest” has to be detected. Secondly individual tree-crowns in this class have to be detected. And the finally the created crown polygons are processed to produce meaningful information for modelling species habitat selection behaviour.

2.4.2. e-Cognition Developer 64; Extracting “Forest” class

In the first step, a multi-resolution segmentation was applied to simplify the image by cutting it into smaller meaningful objects. Here the pixels were mixed based on their homogeneity (Baral, 2011).
For controlling the average object image size, an optimum scale parameter was introduced to the software

through trial and error to find a balance in grouping pixels. So the produced segments were neither too many nor too few.
Then the neighbouring image objects were merged with layer mean intensities below the maximum spectral difference value. This optimum value was also achieved through trial and error.

Finally, 4 different classes were introduced using combination of "Brightness" and "Mean layer 2" as thresholds. The defined classes were "Bareland", "Forest", "Shadow", and a mixture of "Grassland-Tree-Bareland".
"Brightness" was used in the first attempt of classification and then "Mean layer 2" was applied on 2 classes of "Shadow" and "Grassland-Tree-Bareland" to assigned remained patches of forests within these classes to the class "Forest".

OBIA hierarchy was stopped at classification step and the class of "Forest" was extracted as a Polygon shapefile. Further analyses for detecting single trees were carried out in ArcMap.

The thresholds and settings that were used for segmentation and classification are summarised in Table 1 and Table 2.

Figure 8 on the following page illustrates the window in eCognition Developer software for performing image classification with algorithms and thresholds defined in Table 1 and Table 2.

Table 1. Threshold values for classification in eCognition.

Class	**Feature**	**Domain**	**Value**
Shadow	Brightness	Unclassified	< = 59
Grassland-Scatter trees-Bare land	Brightness	Unclassified	135 <= & <= 180
Bare land	Brightness	Unclassified	> 180
Forest	Brightness	Unclassified	59 < & < 135
Forest	Mean layer 2	Shadow	> = 49
Forest	Mean layer 2	Grassland-Tree-Bare land	< 148

Table 2. Threshold values in algorithms applied in eCognition.

Algorithm	**Settings**
Multi-resolution segmentation	Scale Parameters: 10 Shape: 0.5 Compactness: 0.8
Spectral difference segmentation	Maximum spectral difference: 2

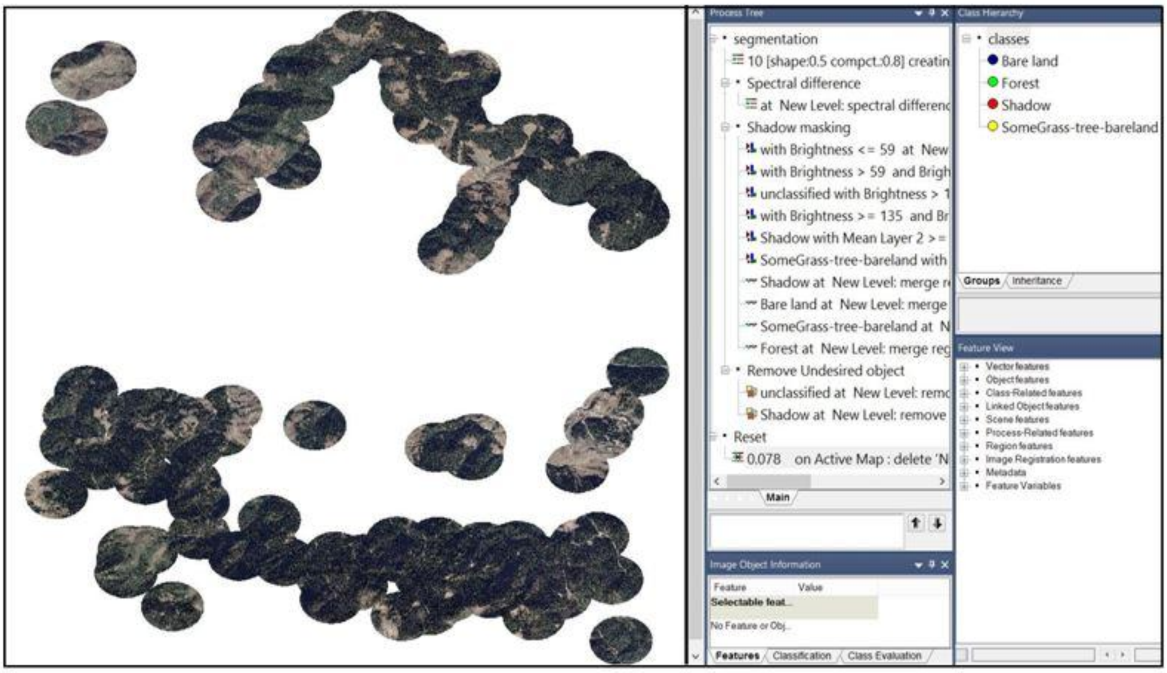

Figure 8. eCognition window to perform classification of "Forest".

2.4.3. ArcMap, Tree Crown Detection

The polygons indicating Forest were extracted from the image. A condition was specified that pixel values between 60 and 130 of the green band could be considered as actual trees. The resulting polygons included a few cluster of trees but mainly individual trees.

To address the objectives of this study the number of trees with a specific crown diameter had to be derived. So clusters of trees that were delineated with one polygon, or very small trees were not needed as input. Such unwanted polygons were removed based on their diameter. The diameter was based on the area of a polygon and assuming it had a circular shape. First, the polygons with a diameter larger than 14 meters were removed. This threshold was according to reporting on stand properties of Rhodopes Forest (Zlatanov et al., 2012) that recognized largest crown diameter in the study area to be around 14 meters.

The raster image of class "Forest" was masked for the second time by the final chosen polygons. The result was a raster image containing only trees and small pieces of grasslands with few scatter trees. To eliminate these small areas, pixel values of less than 119 were chosen as actual trees of the interest. Then the raster image was shrunk by 10 cells to separate adjacent polygons and draw a distinct border around each polygon (tree crown).
Finally polygons with diameter less than 3 meters were removed.

Figure 9 illustrates the approach to detect and extract individual tress with diameter of interest from high resolution aerial image of study area.
Figure 10 illustrates a zooming into single tree detection procedure.

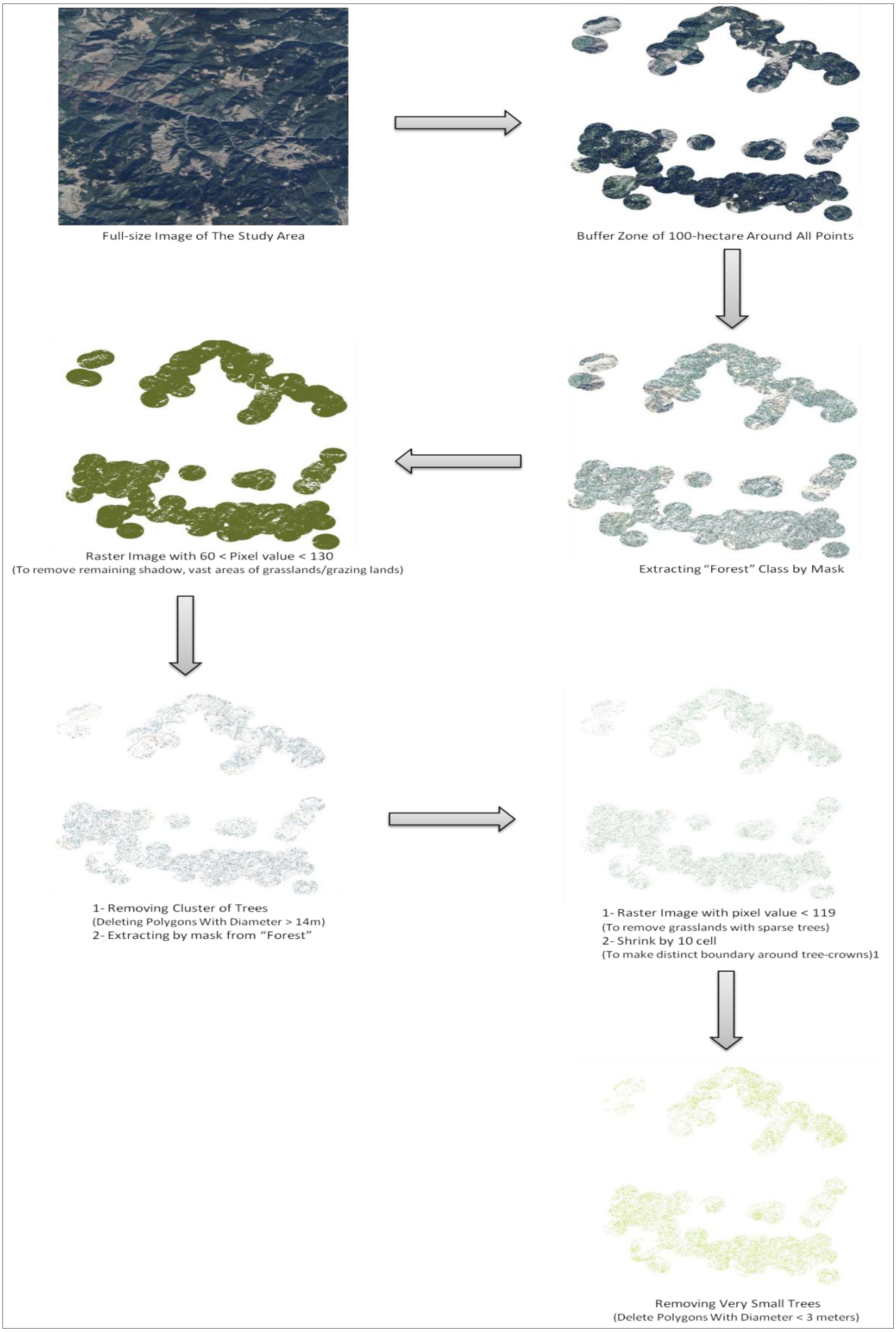

Figure 9. Individual Tree-Crown delineation diagram from high resolution imagery using eCognition and ArcMap.

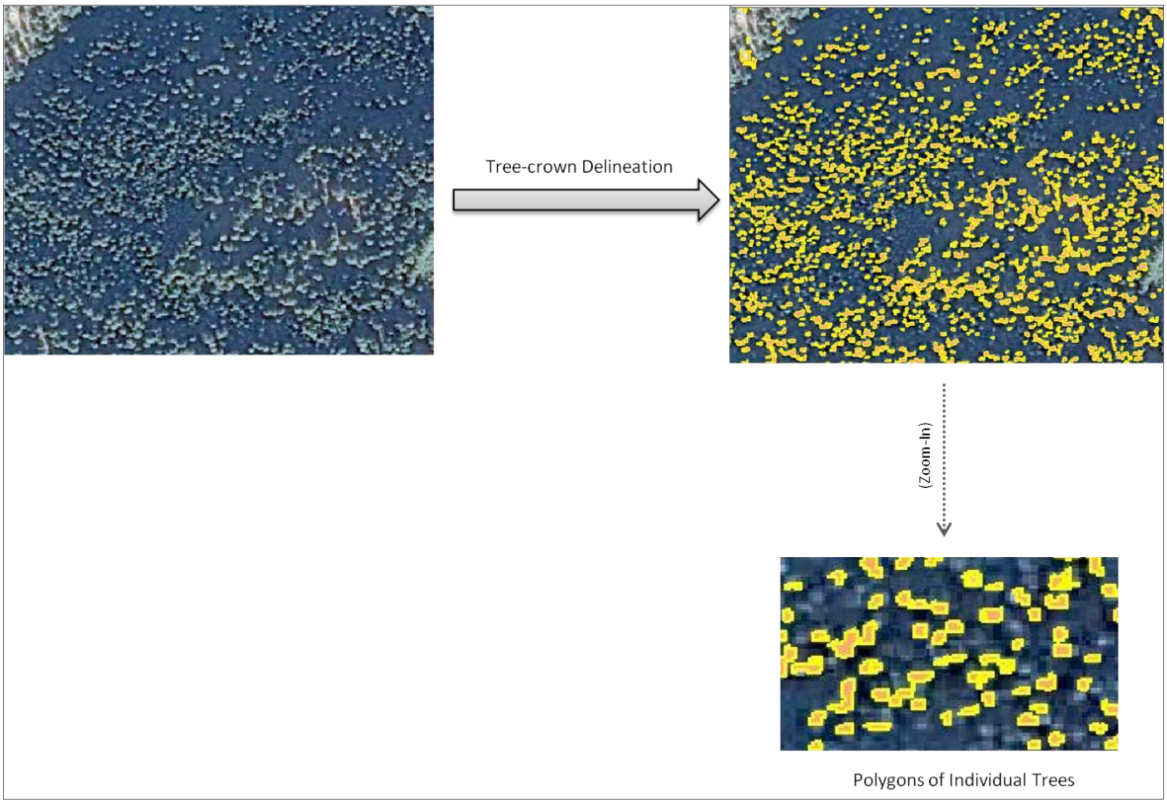

Figure 10. Zoom- In to Individual Tree-Crown delineation Procedure.

Next step was counting number of polygons that fell inside a buffer zone of 100 hectare around each point. From image processing procedure two tables were generated including number of trees with their crown width values and distance to presence/absence point of *A. funereus* and *G. passerinum* in 100 hectare.

Then summary statistics were calculated for the final tree polygons for area of 25, 50 and 100 hectares around each presence and absence point (133 points). These statistics included total number of trees with crown diameter larger than 3 meters up to number of trees with crown diameter larger than 13 meters (11 values for each home range size).

2.4.4. Manual Delineation of Forest Edge

To create a new feature class representing "Forest Edge", the forest boundary detectable from the aerial photograph of the study area was digitized in ArcMap. These consisted usually either of narrow pathways and roads connecting dwellings and villages, or the boundaries with small villages and grasslands. The total length of these lines in the 25, 50 or 100 hectare area around each presence and absence point was included in the analysis as the length of forest edge. Additionally, the shortest distance between occurrence points to the edge was obtained.

Figure 11 on following page illustrates how the "Forest Edge" was delineated on the high resolution image of the study area.

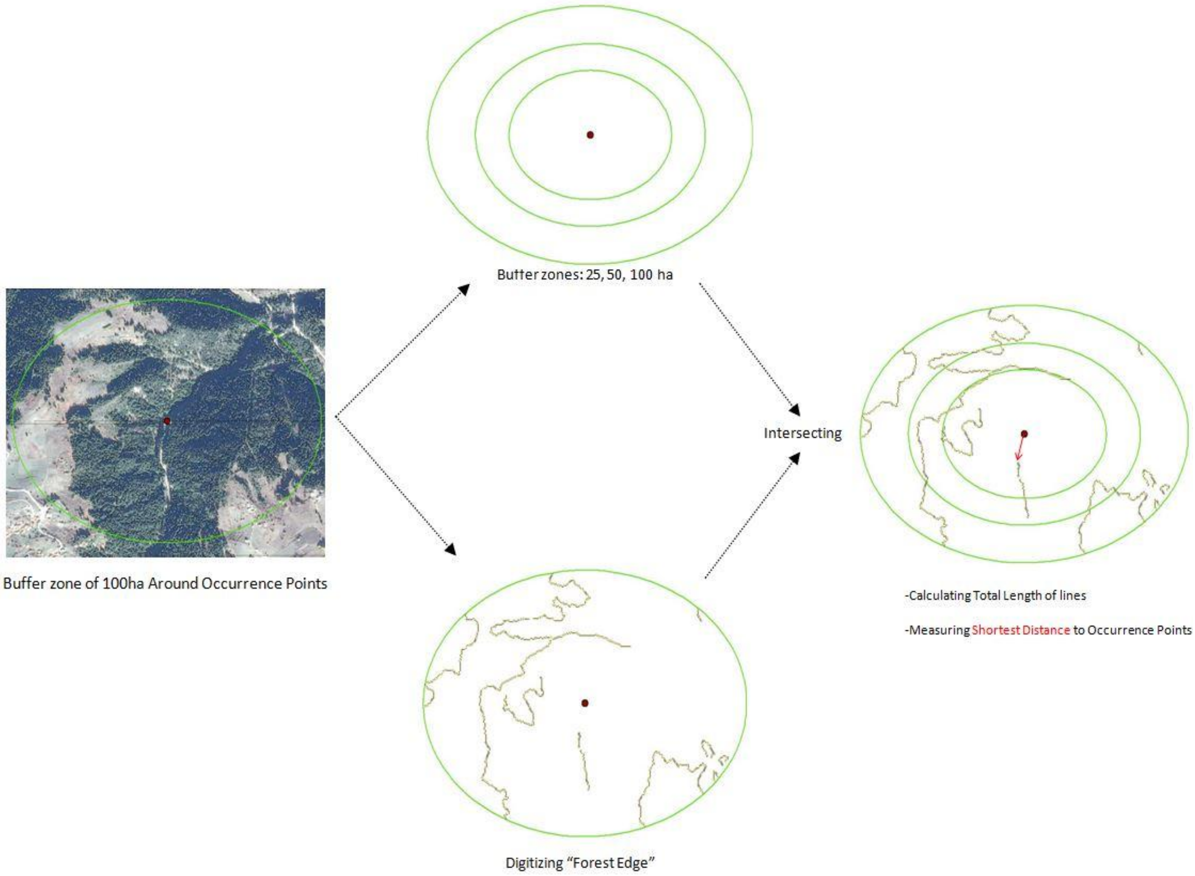

Figure 11. Zoom-In to Extracting "Total Length of Forest Edge" and "Shortest Distance to Edge" Around a Point.

2.4.5. Combining Explanatory Variables and Calculating Density of Trees with Different Crown Diameter

The above image processing yielded 2 datasets, one for each species. These datasets included all presence and absence points of one species, elevation, aspect, slope, shortest distance to forest edge, total length of forest edge within each home range size (3 columns) and total number of trees with crown diameter of more than 3 up to 13 meters (33 columns).

The results of this section are explained in details in Chapter 3, section 3.1.

2.5. Data Analysis and Modelling

For each species (*A. funereus* and *G. passerinum*), each home range size (25, 50 and 100 ha) and each crown diameter size class (3 up to 13 meters) a model was fitted, including the density of trees larger than that size class, and all other variables (slope, aspect, altitude, shortest distance to edge, and total length of forest in that territory size). For these combinations of explanatory variables, two models were used, Generalized Linear Models (GLMs) and Boosted Regression Trees (BRTs). Both models are suitable for presence/absence data.

2.5.1. Multicollinearity Test

Before fitting GLM's and BRT's a collinearity analysis is needed to identify highly correlated pairs of variables. For detecting collinearity, pairwise Pearson's correlation was computed between each combination of predictors. Since pairwise correlation may not be sufficient to detect collinearity, the variance inflation factor (VIF) as a common indicator was calculated. If VIF values exceed 10 as a rule of thumb, the collinearity is so high that it could cause problems when fitting a model and therefore that variable might need to be removed (Myers, 1990).

The variance inflation factor equation is
VIF= $\frac{1}{1-R^2}$ Equation 2

R^2 is the R-squared value of regressing one variable against all the other explanatory variables in the model.

2.5.2. Logistic Regression, Generalized Linear Model

Generalized Linear Model (GLM), as a regression-based model, shows variation in species abundance and they are widely used by ecologists who select explanatory variables according to observed importance (Elith & Leathwick, 2009). Elith, Leathwick, and Hastie (2008) claimed that long time ago, ecologists used linear regression models to find the predictors with most explanatory variables but they were inadequate to explain real life situations. Then in 1980's GLMs became widely popular since they could realistically model nonlinear relationships and analyze presence-absence data which are not normally distributed (Austin, 2007; Leclere, Oberdorff, Belliard, & Leprieur, 2011).

GLM uses logit link and binomial error distribution (Leclere et al., 2011) to fit models with maximum likelihood method. The logit function calculates logarithm of the odds ratio which is the probability of something happening against the probability that it will not.

The equation for odds ratio is $\prod = \frac{P_x}{1-P_x}$ Equation 3
The logit function is the logarithm of below function
f(x)= ln($\prod$)= $\ln(\frac{P_x}{1-P_x})$. Equation 4

For multiple cases f(x)= $b_0 + b_1x_1 + b_2x_2 + \ldots + b_kx_k$ Equation 5

so the Logistic Regression can be written as follows

$P_x = \frac{e^{b_0 + b_1x_1 + b_2x_2 + \ldots}}{1+e^{b_0 + b_1x_1 + b_2x_2 + \ldots}} = \frac{1}{1+e^{-(b_0 + b_1x_1 + b_2x_2 + \ldots)}}$ Equation 6

P_x is the probability of f(x) occurring. where b_0 is the constant and b_1, b_2 and so on are called regression coefficients of x_1, x_2 and so on.

The improvement of the model is computed by adding one or more predictors and the selection of significant variables is done by stepwise algorithm.
Similar to t-test in linear regression, Wald statistics explain if the b-coefficient for the predictors is significantly different from zero. This test assumes difference between maximum likelihood estimate and zero is normally distributed. Then that variable is assumed to make significant contribution to prediction of the result. The equation for Wald statistic is
w= z^2 Equation 7

where z is

z= $\frac{(\alpha - \alpha_0)}{SE(\alpha_0)}$ Equation 8
α is maximum likelihood estimate, α_0 is 0 in summary of GLM (generally the value to compare with) and SE stands for standard error.

Yet Wald statistics should be used by caution when the sample size is small so the standard error might increase. According to Field (2006), in such case, a predictor which contribute significantly to the outcome might be rejected and consider insignificant (Type II error).

2.5.3. Boosted Regression Tree

Elith et al. (2008) believe that Boosted Regression Tree is a flexible regression model that combines statistical power of two algorithms, regression trees and boosting. Regression trees use recursive binary splits to relate response to variables and boosting method combines many simple models to produce a more accurate model with better predictive performance (Elith et al.).

Boosting is a technique for minimizing the loos function by adding a new regression tree at each step that reduces the loos function most (Carty, 2011). The concentration in each step is on reducing the residuals and root mean square error. In the second step, a regression tree which might have different variables and split points with the initial one is fitted to the prediction residuals of the first regression tree. Now the final model has two trees and the residuals from this model are calculated so that this process continues. This is called a stagewise procedure since the existing trees are unchanged as the model increase.
Finally, the result is a BRT model which is a linear combination of hundreds to thousands of trees. This final model is like a regression model where each tree represents a term. (Elith et al., 2008)

$$G(x)= \text{sign} \left(\sum_{m=1}^{M} a_m G_m (x) \right) \qquad \text{Equation 9}$$

$a_1, a_2, \ldots, a_M$ are computed by boosting algorithm, and weight the contribution of each respective G_m (x). Data modification at each step is by applying weights $w_{m1}, w_2, \ldots, w_N$ to each training observation (x_i, y_i) where i= 1, 2, …, N.

BRT also use logit link function like Logistic regression.

$$D= -2 \left[\log(\text{likelyhood}_{reduced}) - \log(\text{likelyhood}_{full})\right] \qquad \text{Equation 10}$$

BRT technique has three important parameters; learning rate, tree complexity and number of trees. The first two parameters are defined by the user and the value of last one is determined by their values.
The learning rate (lr) or shrinkage parameter says how much each tree contributes to the growing model. In general a smaller learning rate is preferred since decreasing learning rate increase the number of required trees. Tree complexity (tc) or the number of nods sees if interactions are fitted or not. These two parameters determine the number of trees (nt) required for optimal prediction (Elith et al., 2008).

The “bag fraction” value is also another parameter that can improve model accuracy. The “bag fraction” specifies the proportion of data to be randomly selected without replacement from the training data set at each iteration. Stochasticity improves the speed and precision of the model significantly and reduces over-fitting (Friedman, 2002). The default for this value is 0.5 meaning at each step half of the data is randomly selected.
In the current research, the tree complexity of 5, learning rate of 0.001 and “bag fraction” of 0.5 were used for all BRT models.

2.5.4. Comparison between GLM and BRT

For analysing the data and interpreting the results of this research from different points of view both models were used although BRT seems to deal better with non-linear response than GLM does.

According to Mateo and Hanselman (2014), BRT performance was better than GLM in their research. They claimed that BRT could easily fit non-linear relationship between response and variables. BRT also doesn't need elimination of outliers or transforming data prior to modelling and the effects of relations between variables are automatically handled too.

Figure 12 illustrates how predictions of GLM compare with BRT's. According to Smith (2012), the output of BRT is more precise where GLM-based model might over predict the occurrence. Leclere et al. (2011) also claimed that in their study of comparing different modelling techniques, BRT produced smaller number of low accurate or poor models.

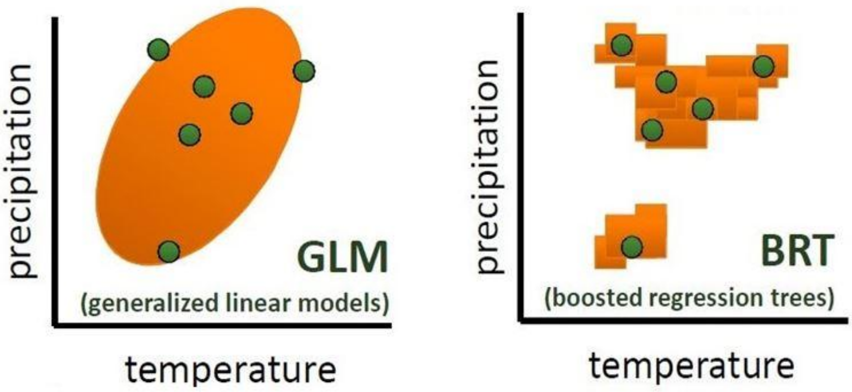

Figure 12. Comparison between GLM and BRT algorithms (Smith, 2012).

2.5.5. Model Evaluation to Choose Best Fitted Model

For evaluating the performance of distribution models it is best to use an independent data set if possible. Since such a data set was not available for this research, the original data was partition into 2 data sets of training and testing, with the proportion of 75-25 respectively. Testing data set was for evaluating the validity of the model fitted with training data set.

As this research was dealing with presence or absence data, MaxKappa from Cohen's kappa (Cohen, 1960) and area under curve (AUC) of receiver operating characteristic (ROC) curve were chosen to measure prediction errors. These two indicators were used for several purposes; finding the best fitted model within each territory size, evaluating impact of different crown diameter classes in modelling habitat selection behaviour of owls, and for comparing the importance of predictors between two species.

Maximum Kappa values were used to measure the accuracy of all models since AUC is not a standard measure of model accuracy. Some scientists argue that AUC does not take predicted probability values and goodness-of-fit of the model into account (Termansen, McClean, & Preston, 2006; Austin, 2007; Lobo, Jimenez-Valverde, & Real, 2008).
AUC values were used to evaluate discrimination capacity of models between locations where one species was present versus locations where it was absent.

For evaluating performance of absence and presence models a confusion matrix is used as a basis which summarizes the model performance (Table 3).

Table 3. Matrix of error.

	Presence	Absence	Total
Presence	a	b	a+b
Absence	c	d	c+d
Total	a+c	b+d	n

where
a is the number of correctly predicted occurrences (True Positive)
b is the number of incorrectly predicted occurrences (commission error) (Type I error)
c is the number of incorrectly predicted absences (omission error) (Type II error)
d is the number of correctly predicted absences (True Negative).

Section 2.5.5.1. described shortly how Cohen's Kappa works and section 2.5.5.2. explained about AUC.

2.5.5.1. Cohen's Kappa

Cohen's kappa is the most popular measure in ecology (Allouche, Tsoar, & Kadmon, 2006) for evaluating accuracy of presence-absence models and it eliminates problem of over estimating accuracy (Liu et al., 2011). Kappa reports the agreement between observers by measuring the proportion of correctly classified observed and predicted locations after accounting the probability of chance only (Freeman & Moisen, 2008).
Kappa equation is:

K_p= (OA – EA) / (1- EA) Equation 11

Where OA stands for overall accuracy and OA and EA equations are

OA= (a+d)/n Equation 12

EA= ($p_{.1} * p_{1.} + p_{.2} * p_{2.}$)/ n^2 Equation 13

where

$p_{.1}$ = (a+c)/n Equation 14

$p_{1.}$= (a+b)/n Equation 15

$p_{.2}$ = (b+d)/n Equation 16

$p_{2.}$= (c+d)/n Equation 17

Kappa is also more resistant to prevalence than other accuracy indicators like sensitivity or specificity (Freeman & Moisen, 2008). A high prevalence increases commission error (Type I error) meaning over prediction and a low prevalence increase omission error (Type II error) which is under prediction.
The formula for prevalence is as below

Prevalence: (a+c)/n Equation 18

Allouche et al. (2006) believe that for identifying biodiversity hotspots in conservation planning, the accuracy evaluation of predicted model should be based on selected threshold. Therefore MaxKappa was employed in this study to deal with prevalence effect to obtain a good model (Santika, 2011).
The maximum kappa value occurs when Kp equals to 1.

MaxKappa equation is:

MaxKp= max(K_p) Equation 19

2.5.5.2. Area Under Curve (AUC)

Receiver operating characteristic (ROC) curve as a threshold-independent measure represents the model's performance in two dimensions. ROC curve plots False Positive Rate (1- specificity) against True Positive Rate (sensitivity). The area under the curve (AUC) summarizes statistic results of a ROC plot. According to Manel et al. (2001) AUC is a good indicator of model performance which shows how good predictions are in models with binary response. AUC is as an independent indicator from prevalence too (Allouche et al., 2006).
The value of AUC ranges from 0 to 1 whereas a perfect discrimination will have an AUC equal to 1.So an AUC value equal to 0.5 indicates that generally the discriminatory is considered not sufficient to be helpful (Scott et al., 2002).The developed formula for AUC (Mason & Graham, 2002) is

$$\mathrm{AUC} = \frac{1}{n_1 n_0} \sum_{i=1}^{n_1} \sum_{j=1}^{n_0} I\,(p_{1i}\,, p_{0j}) \qquad \text{Equation 20}$$

where

$$\mathrm{I}\,(p_{1i}, p_{0j}) = \begin{cases} 0 & \text{if } p_{1i} < p_{0j} \\ 0.5 & \text{if } p_{1i} = p_{0j} \\ 1 & \text{if } p_{1i} > p_{0j} \end{cases}$$

where
p_{1i} is the predicted value for presence site i,
p_{0j} is the predicted value for absence site j,
n_1 is the number of present sites,
n_0 is the number of absent sites (Liu et al., 2009).

2.5.6. Comparison of Importance of Variables Between *G. passerinum* and *A. funereus*

For comparing the importance of explanatory variables in defining suitable habitat for each species in the best fitted model (with highest MaxKappa) in three different home ranges, the percentage of relative importance of each predictor from BRT models, and the most significant variables from GLM models were extracted.

In a BRT model, the relative contribution or importance of variable is calculated by contribution of each variable in reducing overall deviance of the model. The measure is based on how many times a variable is selected for splitting. The relative contribution of each predictor is given in percentage so that the sum adds up to 100 where the higher the number, the stronger the influence of that variable on the response is.

Multiple logistic regression analyses were performed using stepwise procedure to generate models. The output of GLM summary also generates p-values which is probability of getting a value as high or higher than the observed value. The p-values of significant variables in best fitted models were plotted in graphs for interpretation

The contribution of variables in best fitted BRT models for each species are illustrated in graphs in section 3.2.3.
Section 3.2.4. illustrates the significant variables in best fitted GLM models for each species.

2.6. Software and Field Instruments

Technical software employed in this research were Cyber Tracker for field data collection, ArcMap 10.2.1 and eCognition Developer 64 for image processing, and Microsoft Excel and the open-source R-programming language version 3.1.2 for data and statistical analyses.

3. RESULTS

3.1. Image Processing Results

3.1.1. Single Tree Detection

The total number of individual trees detected in 100 hectare around presence/absence points of both species was 1461601. Table 4 shows the density of trees in 100 hectare for each species. These records include trees with different crown diameter from 3 to 14 meters.

Table 4. Total number of trees detected from high resolution imagery in a territory size of 100 hectare.

Absence/ Presence Points of Owl species	Density of Trees
A. funereus presence points	543218
G. passerinum presence points	181697
Absence points of both species	597702
Overlapping presence points	138984
All presence/absence points	Total= 1461601

The table of density of trees also included the shortest distance of each tree to occurrence points (centre of the territory of 100 hectare). According to home range size of interest (100, 50 and 25 hectare), densities of trees within that distance were extracted later using Microsoft Excel and R- software.

3.1.2. Length of Forest Edge

The total length of forest edge in 100 hectare buffer zone around all points (133) was 544820 meters.
By intersecting polyline shapefile of digitized forest-edge with 50 and 25 hectare buffer zones, the total length of forest edge in each territory were calculated as presented below in Table 5.

Table 5. Total length of "Forest Edge" in 25, 50 and 100 hectare territory size.

	Total length of forest opening (m)
25ha	153260
50ha	284963
100ha	544820

Appendix 1, Appendix 2, Appendix 3, and Appendix 4 present maximum, minimum and mean of all predictors that were extracted for *G. passerinum*, *A. funereus*, overlapping points and absence points respectively.
Appendix 8 and Appendix 9 displays abbreviated contents of variables in data set used for modelling *G. passerinum* and *A. funereus* distribution respectively

3.2. Statistical Analyses Results

The collinearity between topographic variables was at acceptable levels so none of them had to be removed from the analysis.
Table 6 and 7 summarize the VIF values of environmental variables that were repeatedly used in

modelling distribution of *G. passerinum* and *A. funereus* in 25, 50 and 100 hectares.
The value of "Total Length of Forest Edge" was changed according to home range size. Crown-diameter classes varied in each of 33 generated models for each species.

Table 6. VIF values of similar explanatory variables among all models on *G. passerinum* distribution in different home range sizes.

	VIF in 25hectare	VIF in 50hectare	VIF in 100hectare
Aspect	1.05	1.06	1.06
Slope	1.15	1.13	1.12
Altitude	1.11	1.1	1.13
Shortest-Distance-Edge	1.56	1.38	1.24
Total-Length-Edge	1.59	1.4	1.25

The maximum VIF for crown-diameter classes in 25 hectare was diameter class of 6 meters with 1.33.
The maximum VIF for crown-diameter classes in 50 hectare was diameter class of 3 meters with 1.36.
The maximum VIF for crown-diameter classes in 100 hectare was diameter class of 3 meters with 1.46.

Table 7. VIF values of similar explanatory variables among all models on *A. funereus* distribution in different home range sizes.

	VIF in 25hectare	VIF in 50hectare	VIF in 100hectare
Aspect	1.04	1.06	1.06
Slope	1.23	1.22	1.2
Altitude	1.07	1.07	1.09
Shortest-Distance-Edge	1.53	1.39	1.23
Total-Length-Edge	1.56	1.39	1.23

The maximum VIF for crown-diameter classes in 25 hectare was diameter class of 3 meters with 1.39.
The maximum VIF for crown-diameter classes in 50 hectare was diameter class of 3 meters with 1.46.
The maximum VIF for crown-diameter classes in 100 hectare was diameter class of 3 meters with 1.51.

Also no significant correlation existed between any pairs of variables that were used as predictors. So distribution models were generated with all variables.
In 25 and 50 hectare home range size in modelling distribution of both species, the maximum pairwise correlation occurred between "Total Length of Forest Edge" and "Shortest Distance to Edge" with 0.52 and 0.43 respectively.
In 100 hectare home range size the maximum correlation value was between "Total Length of Edge" and crown-diameter class of 3 meters. The value was 0.38 in modelling *G. passerinum* and 0.42 in modelling *A. funereus*.

Both GLM and BRT method as well as both AUC and MaxKappa values were used for different purposes. The accuracy indicators of 33 models for each species were calculated to find the crown diameter class and home range size that best predict the distribution of each species. The contribution of significant predictors in occurrence of either species was also compared.

Depending on whether AUC or MaxKappa was used as indicator of accuracy, different models were identified as the best fitting models. But all accuracy indicators had low values and differences were small suggesting that these differences might be due to chance. There was also no consistency in results between GLM and BRT though BRT showed to be more consistent.

The best fitted models were chosen to plot graphs and interpret the result in three different home range sizes.

Section 3.2.1. shows the result for BRT models and section 3.2.2. shows results of GLM models.
In section 3.2.3. MaxKappa values are used as accuracy indicators to study the relative influence of variables in generating most accurate BRT models.
Section 3.2.4. presents most significant variables from GLM models on graphs. MaxKappa is chosen as an appropriate accuracy indicator to find most accurate models. P-values were plotted on graphs with 95% confidence interval. On these graphs, a lower p-value indicates a higher significant level of that predictor.

Appendix 5 shows best fitted BRT models in 25, 50 and 100 hectares with highest MaxKappa values in modelling one species against the other species in all diameter classes.
Appendix 6 and Appendix 7 illustrate how each of 11 crown diameter thresholds in different home range sizes performed as best fitted BRT models with highest MaxKappa values for either species.

3.2.1. Best Fitted Model with Highest Accuracy Indicators with BRT models

For evaluating the impact of variation of crown-width in achieving models with higher accuracy level, both AUC and MaxKappa values were considered to find best fitted BRT models.
Section 3.2.1.1. illustrates best fitted BRT models on *G. passerinum* distribution and section 3.2.1.2. illustrates best fitted BRT models on *A. funereus* distribution with figures.
The crown diameter class of the fitted model is also indicated on each bar.

3.2.1.1. Best Fitted Models for *G. passerinum* Distribution Generated by BRT

The variability of tree diameter classes selected seems to be approximately around 8 meters in different home range sizes from different accuracy indicators.
But no trend is apparent over the home range size that gives better fits in modelling *G. passerinum* distribution.

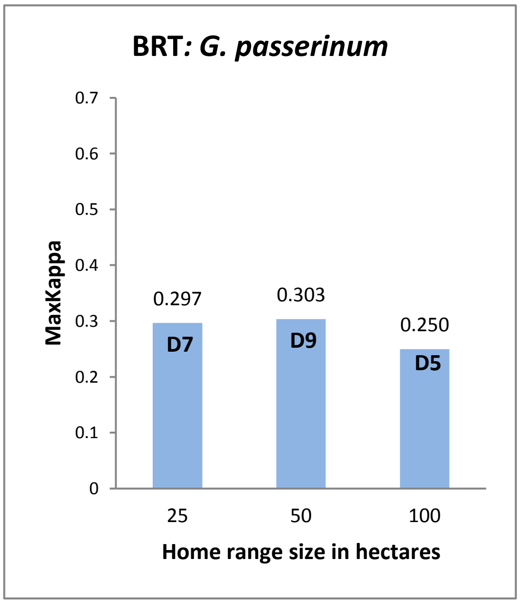

Figure 13. MaxKappa values for BRT models on *G. passerinum* distribution at three different home range sizes with crown diameter threshold used in the fitted model.

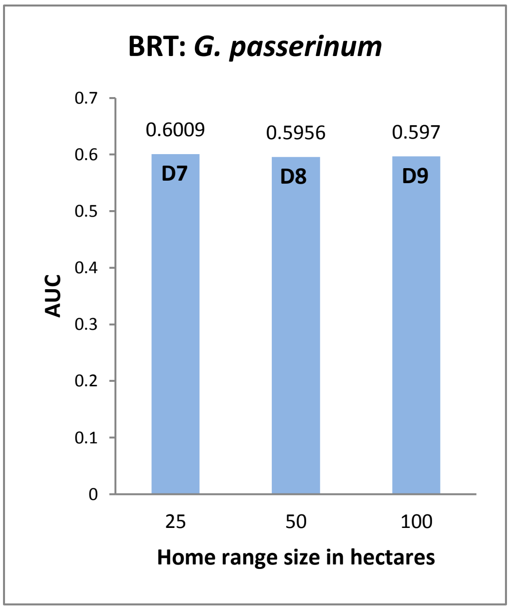

Figure 14. AUC values for BRT models on *G. passerinum* distribution at three different home range sizes with crown diameter threshold used in the fitted model.

3.2.1.2. Best Fitted Models for a. funereus Distribution Generated by BRT

From Figures 15 and 16, it looks like in general *A. funereus* prefer to inhabit trees with larger crown diameter classes with both accuracy indicators.
But there is no trend suggesting a larger home range size would give better fits.

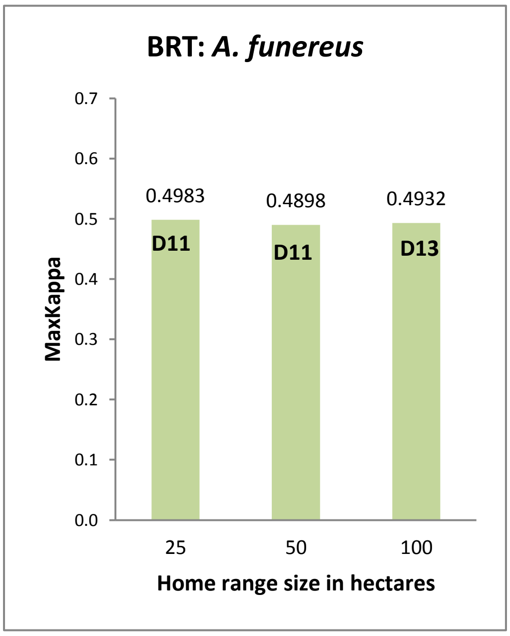

Figure 15. MaxKappa values for BRT models on *A. funereus* distribution at three different home range sizes with crown diameter threshold used in the fitted model.

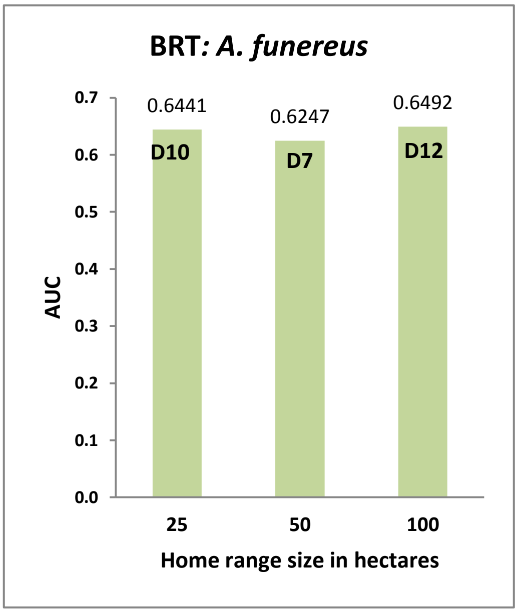

Figure 16. AUC values for BRT models on *A. funereus* distribution at three different home range sizes with crown diameter threshold used in the fitted model.

From Figure 13, 14, 15 and 16, it can be concluded that the accuracy indicators are in general low. There seems to be no trend over home range sizes although diameter classes from best fitted model on *A. funereus* distribution seem to be a bit larger than the ones selected for *G. passerinum*.

3.2.2. Best Fitted Model for *G. passerinum* Distribution with GLM models

This section discussed most accurate GLM models from both MaxKappa and AUC values. Section 3.2.2.1 analyses distribution models of *G. passerinum* and section 3.2.2.2 analyses distribution model of *A. funereus*.

3.2.2.1. Best Fitted Models for *G. passerinum* Generated by GLM

When looking at MaxKappa values it seemed like there are large differences in crown widths selected. But with AUC values, it seems that lower diameter classes are selected.

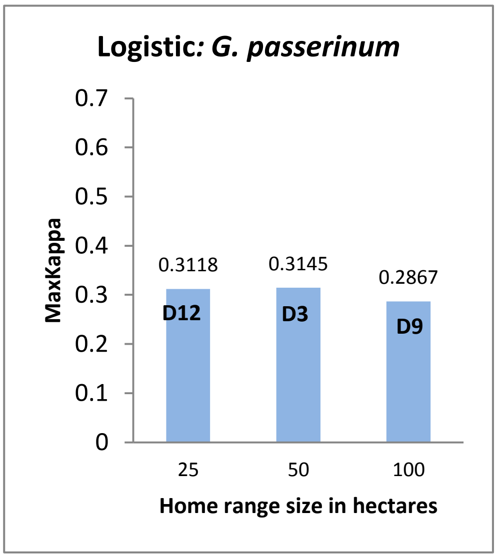

Figure 17. MaxKappa values for GLM models on *G. passerinum* distribution at three different home range sizes with crown diameter threshold used in the fitted model.

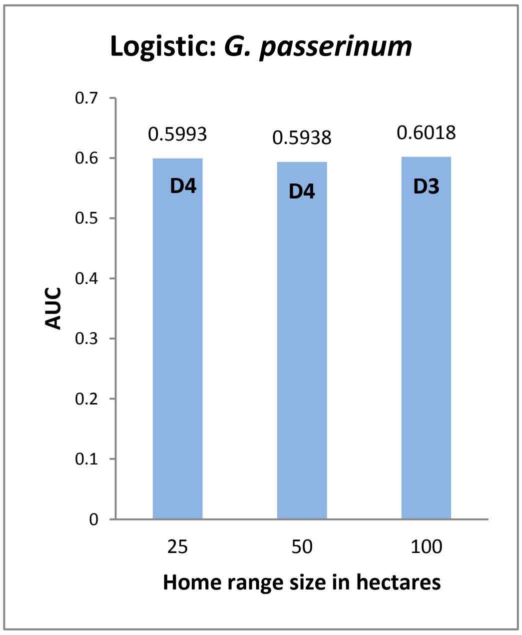

Figure 18. AUC values for GLM models on *G. passerinum* distribution at three different home range sizes with crown diameter threshold used in the fitted model.

3.2.2.2. Best Fitted Models for *A. funereus* Distribution Generated by GLM

In general, from both highest MaxKappa and AUC values in GLM models on *A. funereus* distribution, this species seems to prefer larger tree crown diameter classes.

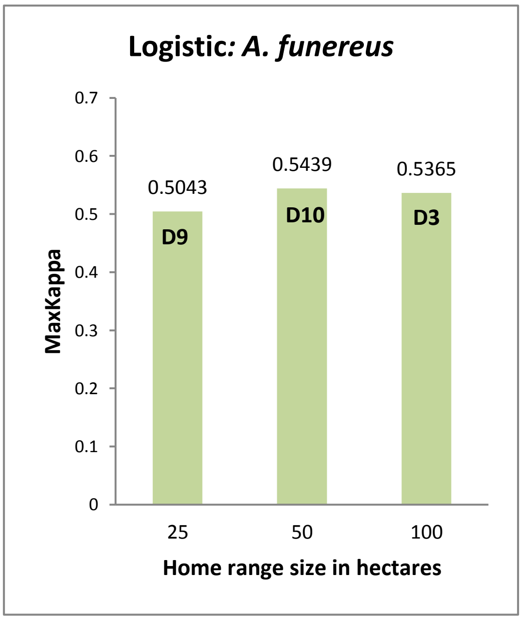

Figure 19. MaxKappa values for GLM models on *A. funereus* distribution at three different home range sizes with crown diameter threshold used in the fitted model.

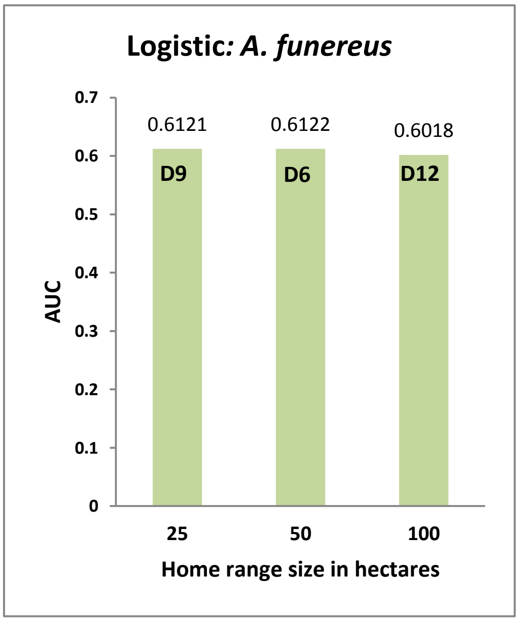

Figure 20. AUC values for GLM models on *A. funereus* distribution at three different home range sizes with crown diameter threshold used in the fitted model.

From Figure 17 ,18 ,19 and 20, similar to BRT models although with more variability, it seems that best fitted *A. funereus* distribution models were based on larger diameter classes than *G. passerinum*.
Also no home range size seems to give better prediction of presence of either species.

3.2.3. Relative Contribution of Predictors From BRT Model

For evaluating the relative contribution (%) of predictors for best fitted BRT models, highest MaxKappa values were chosen as accuracy indicator.

Figure 21 shows relative contribution of predictors for *G. passerinum* and Figure 22 illustrates the contribution of variables in occurrence of *A. funereus*.

3.2.3.1. Relative Contribution of Predictors in Best Fitted BRT Models for *G. passerinum* Distribution

"Slope" contributed most to *G. passerinum* occurrence at all different home range sizes consistently though with a decreasing slope as the territory size decreased.
"Altitude" also scored as the second most important variable at all different home range sizes.

"Shortest Distance to Forest Edge" appeared to be nearly as important as "Altitude" in all three territory sizes and its relative influence remained nearly constant with a slight decreased in largest home range size.
The contribution of "Total Length of Forest Edge" increased as the home range size increased. In 100 hectares, "Total Length of Forest Edge" was most important variable after "Slope" and "Altitude".

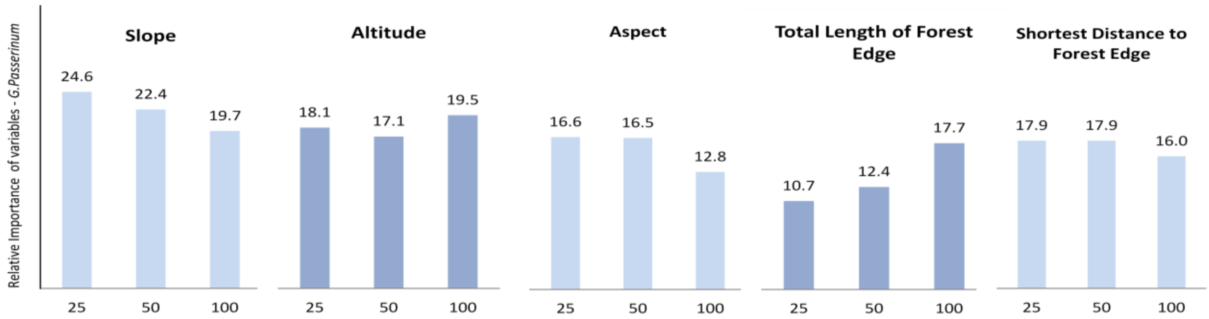

Figure 21. Relative importance of variables from BRT models on *G. passerinum* distribution with highest MaxKappa values at three different home range sizes in hectares

Appendices 10, 11 and 12 illustrate partial dependence plots of BRT models with highest MaxKappa values on distribution modelling of *G. passerinum* in 25, 50 and 100 hectare respectively.

3.2.3.2. Relative Contribution of Predictors in Best Fitted BRT Models for *A. funereus* Distribution

"Slope" contributed most to occurrence of *A. funereus* in all home range sizes with constantly scoring about 30 %. Then "Altitude" scored as the second with a great difference from "Slope".

"Total Length of Forest Edge" was relatively important but with no obvious trend in different home range sizes.
"Shortest Distance to Edge" appeared to have an upward trend but contributed little.

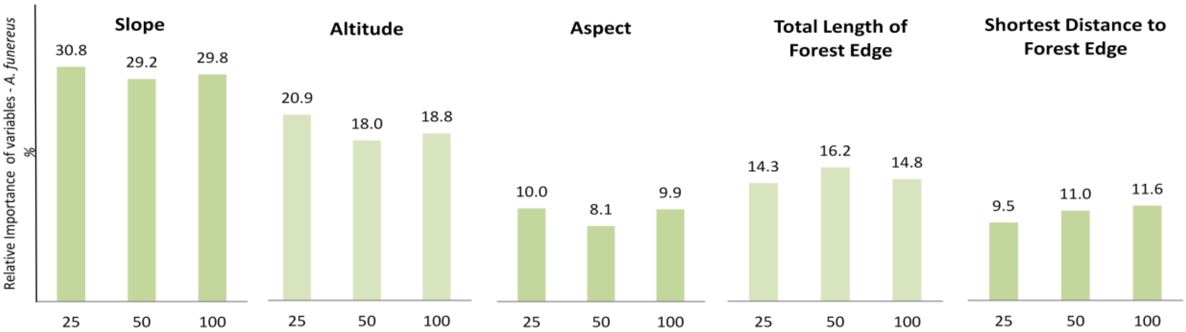

Figure 22. Relative importance of variables from BRT models on *A. funereus* distribution with highest MaxKappa values at three different home range sizes in hectares

From Figure 21 and 22, "Slope" and "Altitude" appeared to be the two most important contributor to occurrence of both species in all home range sizes. Yet in general, both of these variables' contribution was slightly higher in modelling distribution of *A. funereus* than *G. passerinum.*

Appendices 13, 14 and 15 illustrate partial dependence plots of BRT models with highest MaxKappa values on distribution modelling of *A. funereus* in 25, 50 and 100 hectare respectively.

3.2.4. Importance of Variables from Best Fitted Generalized Linear Models

Like section 3.2.3, highest MaxKappa values were chosen as most accurate GLMs. GLM only returns significant variables.
For plotting these variables, their p-values were used. In a maximum likelihood test of GLM, a lower p-value indicates a higher significant level of that variable.

Section 3.2.4.1. illustrates p-values of significant variable in models on distribution of *G. passerinum* and section 3.2.4.2. illustrates p-values of significant predictors for *A. funereus*.

3.2.4.1. Significant Variables from GLM on *G. passerinum Distribution*

The only significant variable in logistic models on *G. passerinum* distribution appeared to be "Slope". This variable was slightly more significant in 50 hectare while it was equally significant in smallest and largest home range size.

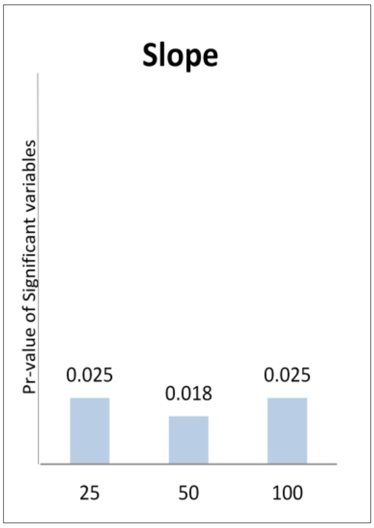

Figure 23. P-values of significant variables from GLM models on *G. passerinum* distribution with highest MaxKappa values at three different home range sizes in hectares.

3.2.4.2. Significant Variables from GLM on *A. funereus* Distribution

"Slope" and "Total Length of Forest Edge" were returned as two significant predictors in modelling distribution of *A. funereus*.
Although "Slope" did not appear to be a significant predictor in smallest home range size, "Total Length of Forest Edge" was most significant in 25 hectare zone.

In general, "Length of Forest Edge" was more significant than "Slope" in both 50 and 100 hectares.

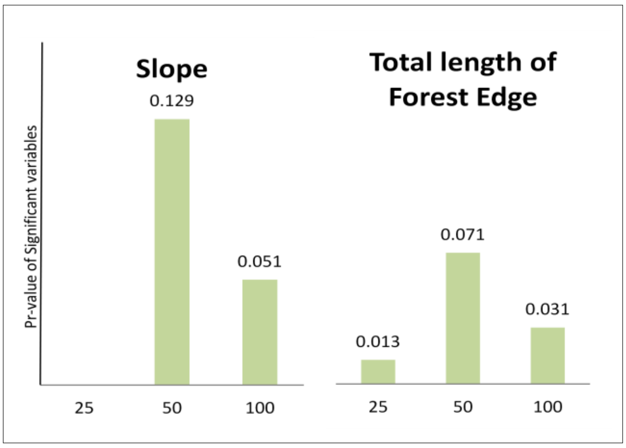

Figure 24. P-values of significant variables from GLM models on *A. funereus* distribution with highest MaxKappa values at three different home range sizes in hectares.

From section 3.2.3. and 3.2.4. "Slope" appeared to be the most important predictor for both species. And "Total Length of Forest Edge" seems to be constantly important for *A. funereus* occurrence over all home range sizes.

4. DISCUSSION AND CONCLUSION

As mentioned earlier, modelling *G. passerinum* and *A. funereus* distribution with ground truth data did not generate highly accurate results to explain confidently the contribution of predictors. The accuracy of generated models with selected environmental variables derived from high resolution imagery was not high enough either. This could be due to several reasons,

-The right variables were not included
-The range of values for the relevant variables was not right
-There was a lot of error in the data
-The species are generalists and did not respond top strongly to any variables

Also by comparing the accuracy indicators between distribution models of each species, both MaxKappa and AUC values were in general consistently higher in modelling *A. funereus* distribution. But there was more inconsistency in crown diameter class selected in modelling *G. passerinum* distribution. This might indicate that niche modelling of *G. passerinum* is more challenging and needs further information of their habitat like height or DBH of the trees, food availability or presence of other predators.

However, it seems like SDMs of these species with image derived proxies of stand structure can explain the ecology of these birds to some extent. The results were in line with previous findings on importance of tree crowns and slope in explaining presence of both owl species; as well as indicating importance of factors like "Forest Edge" which was introduced as a new variable in western Rhodopes Mountains.

This section discusses how each of the explanatory variables that were used in generating distribution models explained habitat requirements of either of owl species.

4.1. Correlation between topographic variables and Owls' presence

"Slope" appeared to be the most significant predictor in occurrence of both *G. passerinum* and *A. funereus* from best fitted BRT and GLM models. The relative importance of "Slope" scored highest in all three home range sizes for both species. This result confirms reporting their occurrence in steep terrains in many surveys. Yet it was interesting that GLM on *G. passerinum* distribution only returned "Slope" as the significant variables over all home range sizes.

Aspect was converted to westness and it was expected to be significantly correlated to occurrence of *A. funereus*. However "Westness" appeared to be the least important predictor for this species while around 70% of *A. funereus* territories were reported on western slope (Rajkovic et al, 2013) and the result contradicted with the findings of other studies that reported their presence on west facing slopes (Shurulinkov et al, 2012).
So it seems like western Rhodope provides *A. funereus* with a suitable habitat regardless of aspect as the dense and old forest of Rhodope Mountains provides enough shadow and dim environment for this species.

On the other hand it seems like the importance of "Westness" for *G. passerinum* was higher than for *A. funereus*. This can be explained by the fact that sunlight reaches west facing slopes later than east facing slopes, so western slopes are cooler for longer period of time during the day until sunlight reaches there in the afternoon. It is known that *G. passerinum* prefers cold-weather regions and their occurrence was recorded after sunrise and during daylight in several studies since they cannot hunt in total darkness. Thus it can be assumed that westness provides *G. passerinum* with more favourable temperature condition for a longer hunting period.

It was expected for elevation to be a more important predictor in explaining presence of *G. passerinum* than in *A. funereus* distribution modelling. *G. passerinum* is generally known as "birds of higher altitude" and the range of altitudes reported for occurrence of *A. funereus* from previous studies were quite wide. But from the relative importance of "Altitude" from best fitted BRT models of this study, "Altitude" was equally important for both species as the second most important predictor.

In general, the results of modelling distribution of owl species in western Rhodope is not exactly the same as surveys conducted in North America, Canada or even Norway.
This inconsistency in reporting most important predictors in occurrence of either owl species might be due to the latitudinal effect. The relationship between environmental variables and owl distribution varies with latitude. So a variable which is significantly correlated to species occurrence might not be equally significant in other regions of the world or vice versa. In this case Bulgaria is in much lower latitudes, comparing to Norway or Canada, that aspect does not seem to effect habitat selection of owls.

It also looks like we are dealing with interaction effect between variables. Interaction of topographic variables with stand structure variables can affect habitat preference of either species. For instance environmental conditions change over altitude and interaction of altitude with other variables can make a variable more significant in one region than other areas of occurrence. Thus generalisation of ecology and behaviour of these species must be done with caution.

4.2. Importance of "Forest Edge" in habitat selection behaviour

Predictors related to "Forest Edge" were introduced to modelling distribution of these species in Rhodopes Mountains for the first time. When dealing with effect of "Forest Edge" on habitat selection of animals, the term in general refers to two main factors, availability of food, and forestry activities. Both of these factors influence the presence or absence of owl species.

According to initial hypothesis, "Shortest Distance to Edge" was expected to have significant correlation with occurrence of *G. passerinum.* This hypothesis was derived from the theory that forest edge provides higher density of preys and *G. passerinum* as a diurnal owl species tends to inhabit areas closer to forest-edge so that this species can detect preys easier. It is also known that *G. passerinum* is more tolerant to forestry activities and being close to forest openings doesn't disturb them as much as it disturbs *A. funereus*.
The importance of this variable for occurrence of *G. passerinum* was confirmed by results from relative importance of "Shortest Distance to Edge" from best fitted BRT models. The value was relatively as high as "Altitude" (as the second most important predictor) and it did not fluctuate over different home range sizes.

On the other hand, it is known that *A. funereus* is more reluctant to nest close to sites of human activity. The values of relative importance of "Shortest Distance to Edge" in modelling distribution of *A. funereus* scored very low as well.
Although it needs further investigations to define appropriate threshold on how close to edge either species would like to be.

It was expected that "Total Length of Forest Edge" to be an important factor for *A. funereus*. This hypothesis was derived from literature saying that *A. funereus* need access to longer forest edge (comparing to *G. passerinum)* to have more successful prey capture.
The hypothesis was confirmed by the outputs of best fitted GLMs that returned "Length of Forest Edge" as a significant predictor along with "Slope".
This variable was also the third most important predictor after "Slope" and "Altitude" from BRT models on distribution of *A. funereus*

4.3. Tree-crown Diameter Class

According to literature on the ecology of these birds, their occurrence is related to forest cover, tree crowns and diameter at breast height.
The accuracy indicators were not as strong as was expected and the inconsistency between best fitted models from highest MaxKappa values and highest AUC values made it difficult to conclude what crown-width could explain owls occurrence best.

However, in general, *A. funereus* occurrence showed a higher dependency on larger crown diameter classes than *G. passerinum* which confirmed the previous knowledge of habitat selection behaviour of *A. funereus* to nest on old trees with larger DBH (thus with a larger crown width).

On the other hand, a variability of diameter classes was selected in modelling *G. passerinum* distribution. If we consider higher tree-cover and larger crown-diameter as indicator of age of the trees, then smaller crown width might imply existence of younger trees. So variability in crown diameters selected from best fitted models seems to indicate that only old trees are not suitable, but only young trees neither. But a mix of old and young trees suits *G. passerinum*. So a large variability and consequently standard deviation in crown diameter size indicates their suitable habitat.
This result is also in line with previous studies that reported *G. passerinum* nesting holes on very old trees that were surrounded with (younger) trees with regeneration. Because such environment provides plenty number of birds to be preyed upon for *G. passerinum* (Ström and Sonerud, 2001).

4.4. Home range size

There was no trend across home range sizes from best fitted models with AUC or MaxKappa values in different scales. The large erratic fluctuation made it difficult to conclude which of the three studied home range size would explain *G. passerinum* or *A. funereus* occurrence best.
So the scale for analysing the data needs to be adjusted in further studies to be more representative of their actual territory size.

5. RECOMMENDATION

The following recommendations are suggested to generate more accurate models from image derived variables and to reduce the error in data in further studies.

1. Possible fluctuation in food supply can affect foraging site selection of owls. Thus it is recommended to consider the availability of food or breeding season in modelling habitat selection behaviour. For example, correlation between occurrence and "Forest Edge" related variables might change if there would be reduced food availability within the dense forest.

2. It is recommended not to limit the importance of "Aspect" just to westness. Northness could also be relevant since in northern hemisphere north facing slopes receive less solar heating.

3. The current environmental predictors might have not been sufficient to model owls distribution accurately. So considering other predictors such as age, height and DBH of the trees, density of understory cover, food availability, presence of competitors and presence of predators might improve prediction capacity of distribution models.

4. The purpose of the study was to test accuracy of generated model from information extracted by RS techniques. Crown shape or tree species can be derived from aerial photographs. If tree-parameters like its height could be extracted too, it would help in correlating CPA to DBH and age of the trees. Having such recognised predictors in their occurrence could increase model accuracy significantly.
For instance using LiDAR data might prove very useful as it gives 3D information of the trees. Then with CPA values and tree-height, corresponding DBH can be calculated as well.

Calibrating the image processing results to field measurements of validation stands can also reduce the error in data and improve accuracy of generated models.

5. It is recommended to examine model accuracy in different scales starting from 100 hectares as the average recognized territory size and expanding it to 400 hectares as the largest recognized home range size. A larger scale that contains more information on suitable environmental conditions for owls occurrence might predict their presence better.
But to find the proper scale that explains owls presence best, repeating the same study in other areas with similar environmental conditions is suggested.

6. It is strongly recommended to consider interaction effects between environmental variables used in generating distribution models. Altitude might be interacting with distance to forest edge or tree crown width. As a result, different variables might take priority over one another in different environmental conditions.

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Appendix 1. Brief summary of variables for presence points of *G. passerinum*

Slope	Minimum	8
	Mean	19.9
	Maximum	42.3
Altitude	Minimum	1385
	Mean	1659
	Maximum	1966
Aspect	Minimum	2.5
	Mean	91
	Maximum	166.8
Shortest Distance to Edge	Minimum	6
	Mean	78.9
	Maximum	228.5
Total Length of Forest Edge- 25 ha	Minimum	217
	Mean	1073.1
	Maximum	2297
Total Length of Forest Edge- 50 ha	Minimum	487
	Mean	2017.1
	Maximum	4817
Total Length of Forest Edge- 100 ha	Minimum	1433
	Mean	3948
	Maximum	10350

Appendix 2. Brief summary of variables for presence points of *A. funereus*

Slope	Minimum	3.9
	Mean	19.5
	Maximum	38.9
Altitude	Minimum	1218
	Mean	1658
	Maximum	2105
Aspect	Minimum	0.7
	Mean	91.7
	Maximum	177.8
Shortest Distance to Edge	Minimum	0
	Mean	64.1
	Maximum	272.88
Total Length of Forest Edge- 25 ha	Minimum	78
	Mean	1027
	Maximum	2227
Total Length of Forest Edge- 50 ha	Minimum	387
	Mean	1929
	Maximum	4709
Total Length of Forest Edge- 100 ha	Minimum	1103
	Mean	3771
	Maximum	8193

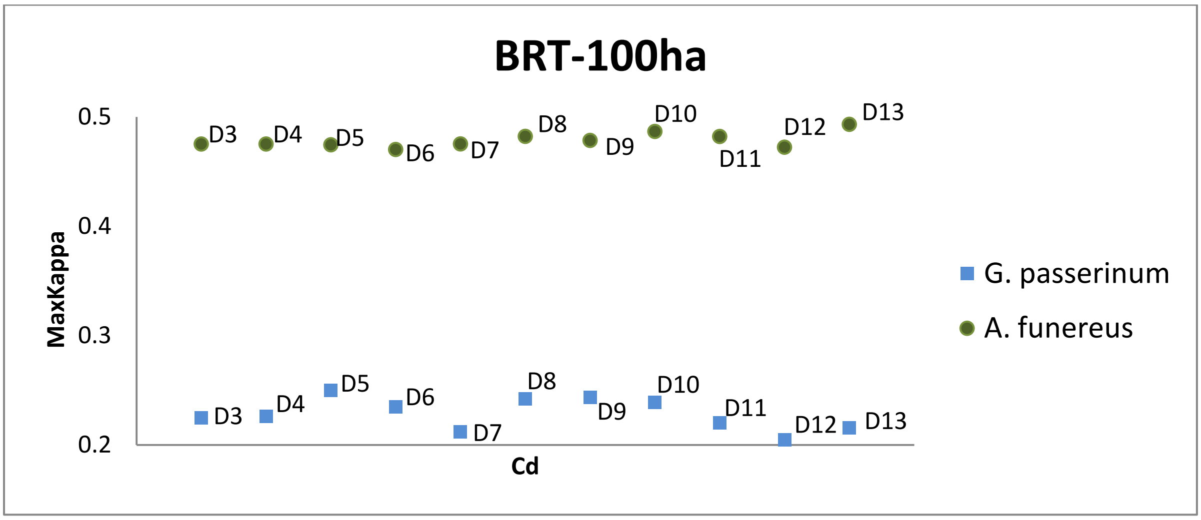
Appendix 3. Brief summary of variables for overlapping presence points

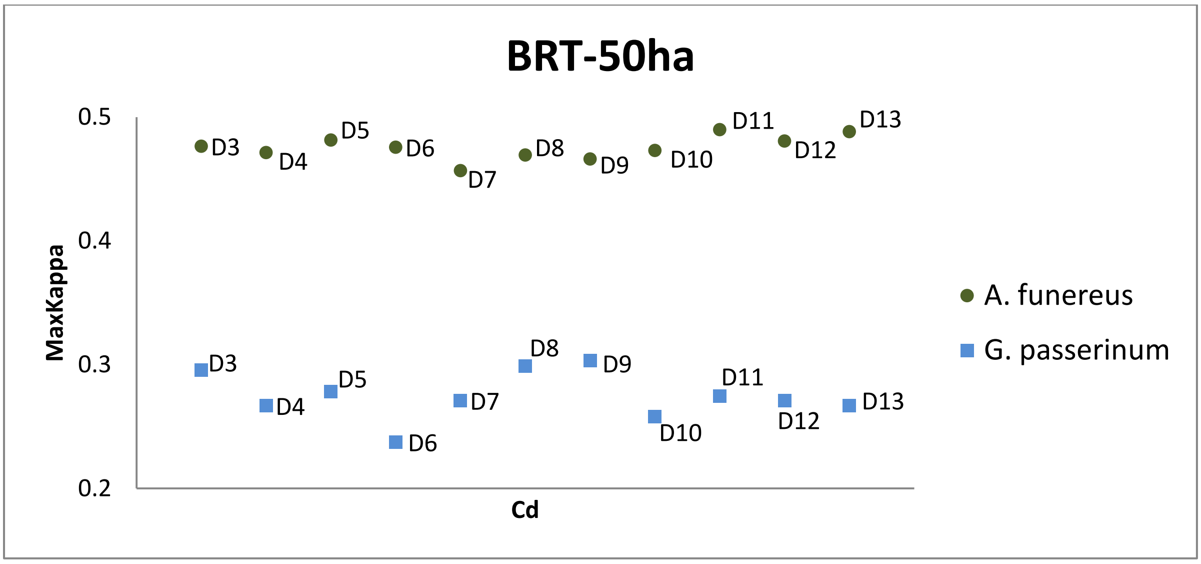
Slope	Minimum	8.3
	Mean	23.04
	Maximum	40.9
Altitude	Minimum	1363
	Mean	1614
	Maximum	1837
Aspect	Minimum	9.6
	Mean	91.1
	Maximum	169.3
Shortest Distance to Edge	Minimum	6.5
	Mean	108.6
	Maximum	397.2
Total Length of Forest Edge- 25 ha	Minimum	0
	Mean	775.2
	Maximum	2155
Total Length of Forest Edge- 50 ha	Minimum	3
	Mean	1490
	Maximum	5033
Total Length of Forest Edge- 100 ha	Minimum	911
	Mean	3074
	Maximum	8378

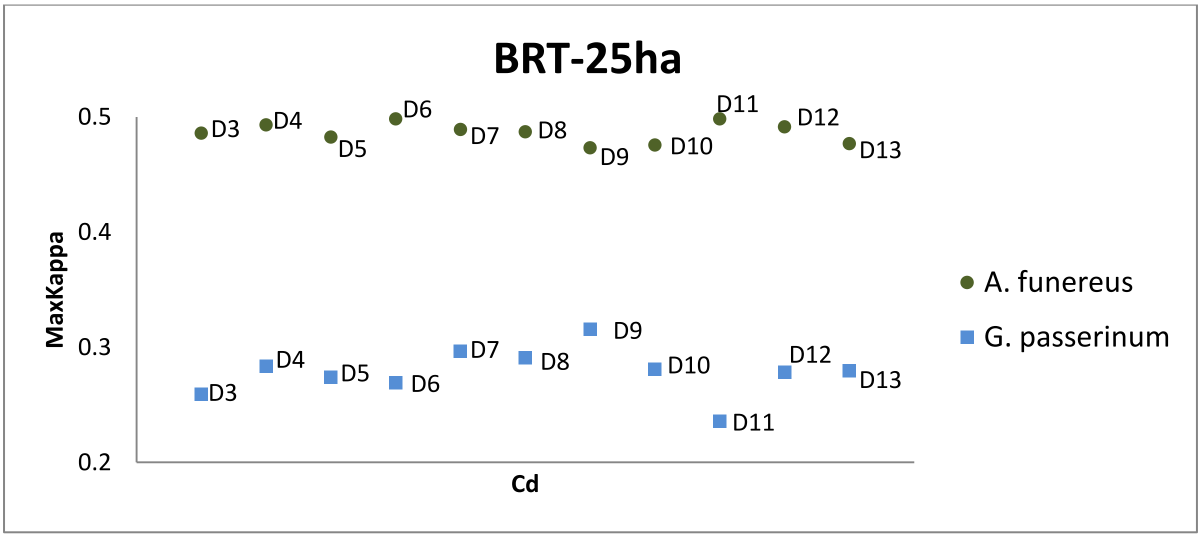
Appendix 4. Brief summary of variables for absence points

Slope	Minimum	2.06
	Mean	14.1
	Maximum	34.5
Altitude	Minimum	1259
	Mean	1645
	Maximum	1979
Aspect	Minimum	904
	Mean	104.6
	Maximum	177.4
Shortest Distance to Edge	Minimum	0
	Mean	39.51
	Maximum	249.6
Total Length of Forest Edge- 25 ha	Minimum	40
	Mean	1384
	Maximum	3001
Total Length of Forest Edge- 50 ha	Minimum	490
	Mean	2537
	Maximum	6187
Total Length of Forest Edge- 100 ha	Minimum	1535
	Mean	4692
	Maximum	9946

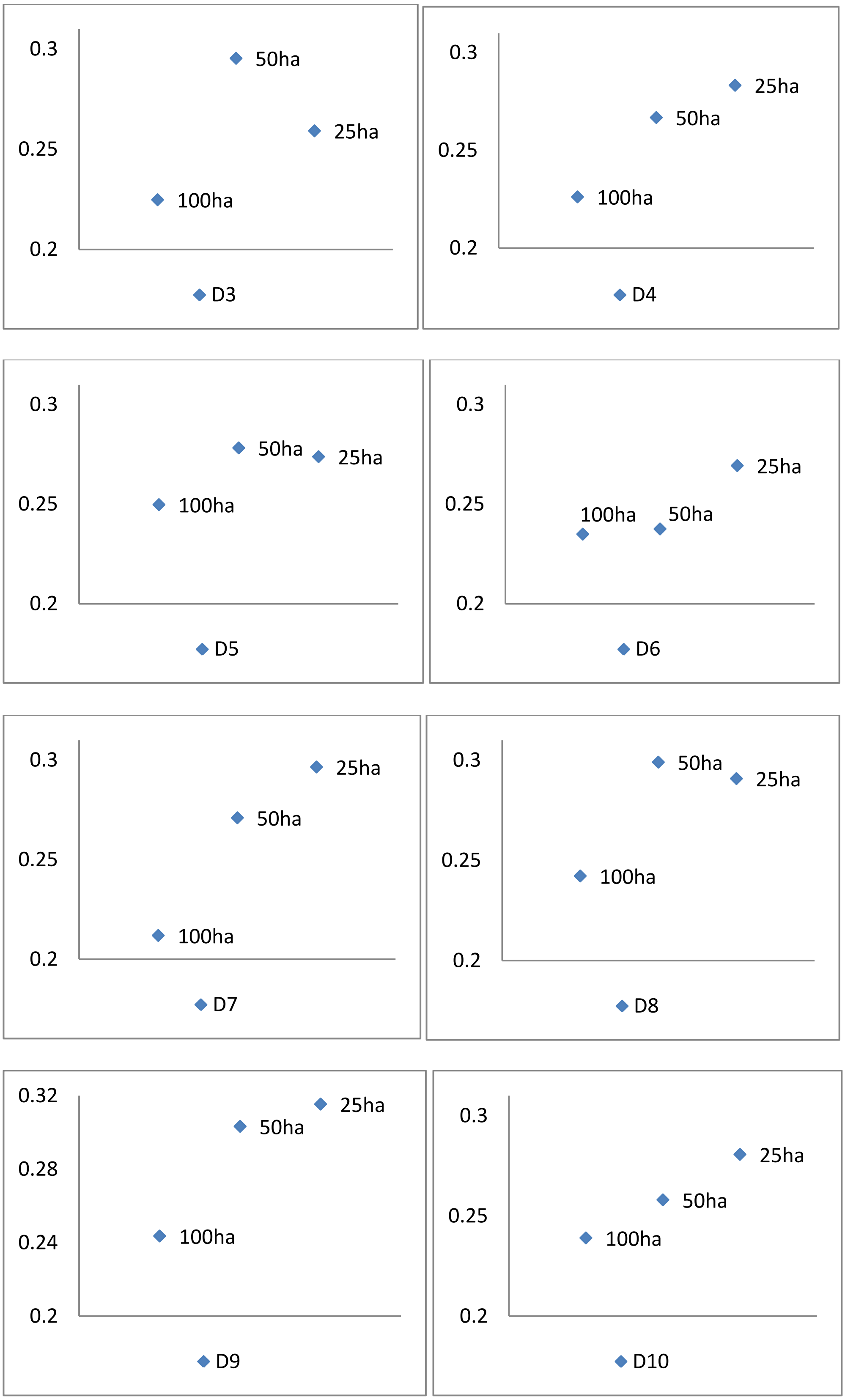
Appendix 5. Comparison between best fitted BRT models with highest MaxKappa values in distribution modelling of *G. passerinum* and *A. funereus* with crown diameter thresholds used in fitted models

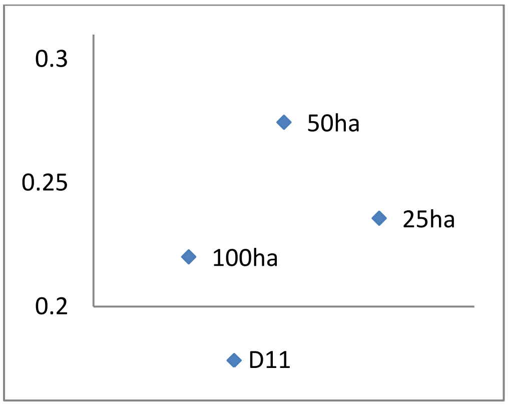


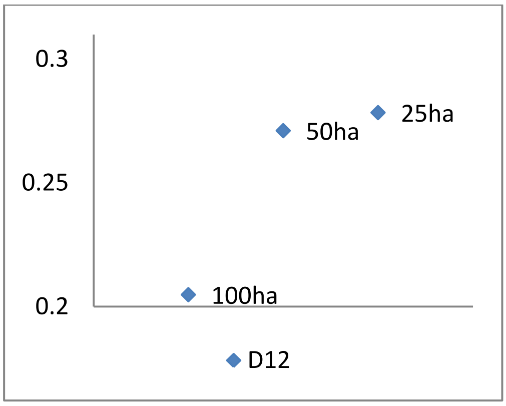


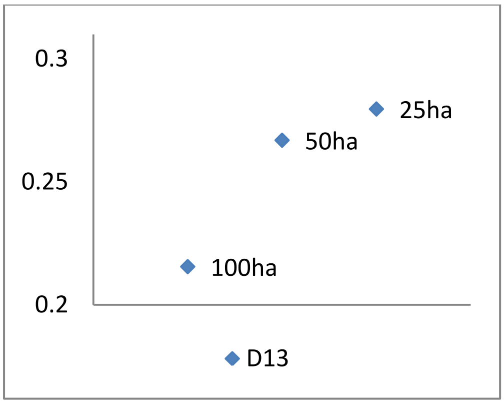


Appendix 6. Comparison between response of different crown diameter classes over different territory sizes in hectares from highest MaxKappa values in BRT models on *G. passerinum* distribution

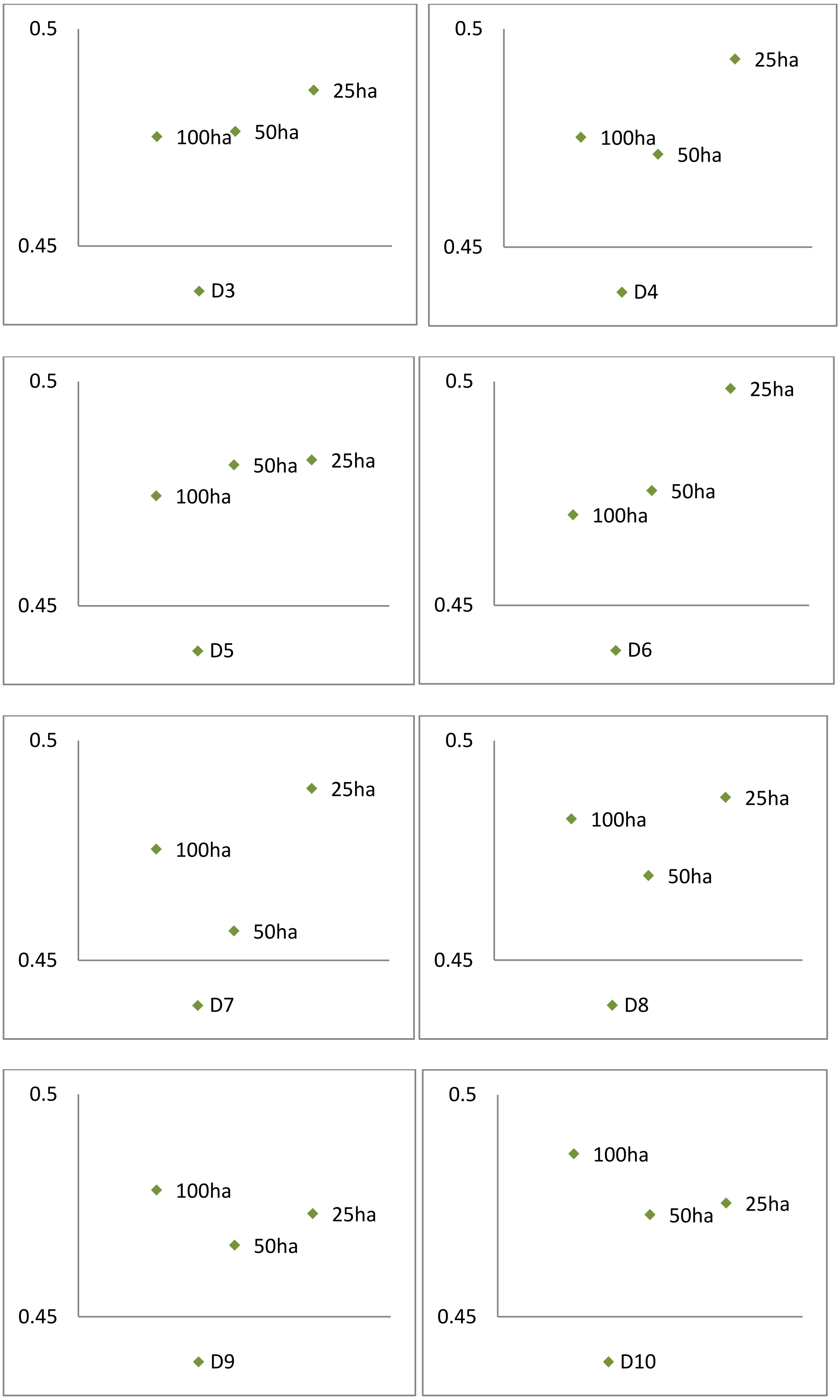


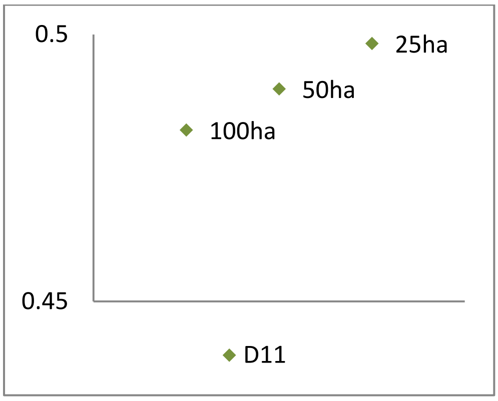

0.3
50ha
0.25
25ha
100ha
0.2
D11

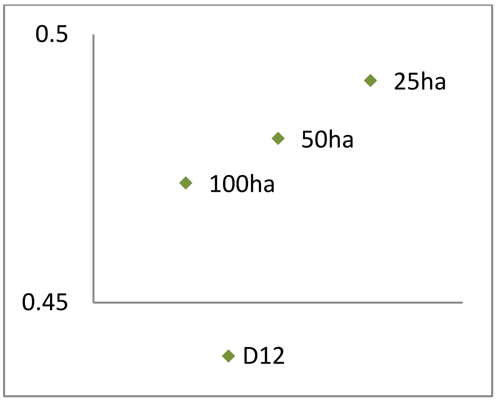

0.3
25ha
50ha
0.25
100ha
0.2
D12

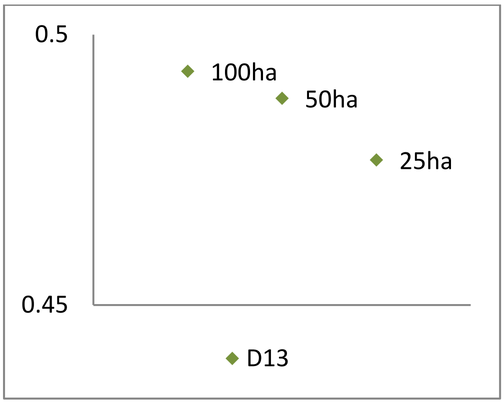

0.3
25ha
50ha
0.25
100ha
0.2
D13

Appendix 7. Comparison between response of different crown diameter classes over different territory sizes in hectares from highest MaxKappa values in BRT models on *A. funereus* distribution




0.5
25ha
50ha
100ha
0.45
D11


0.5
25ha
50ha
100ha
0.45
D12


0.5
100ha
50ha
25ha
0.45
D13

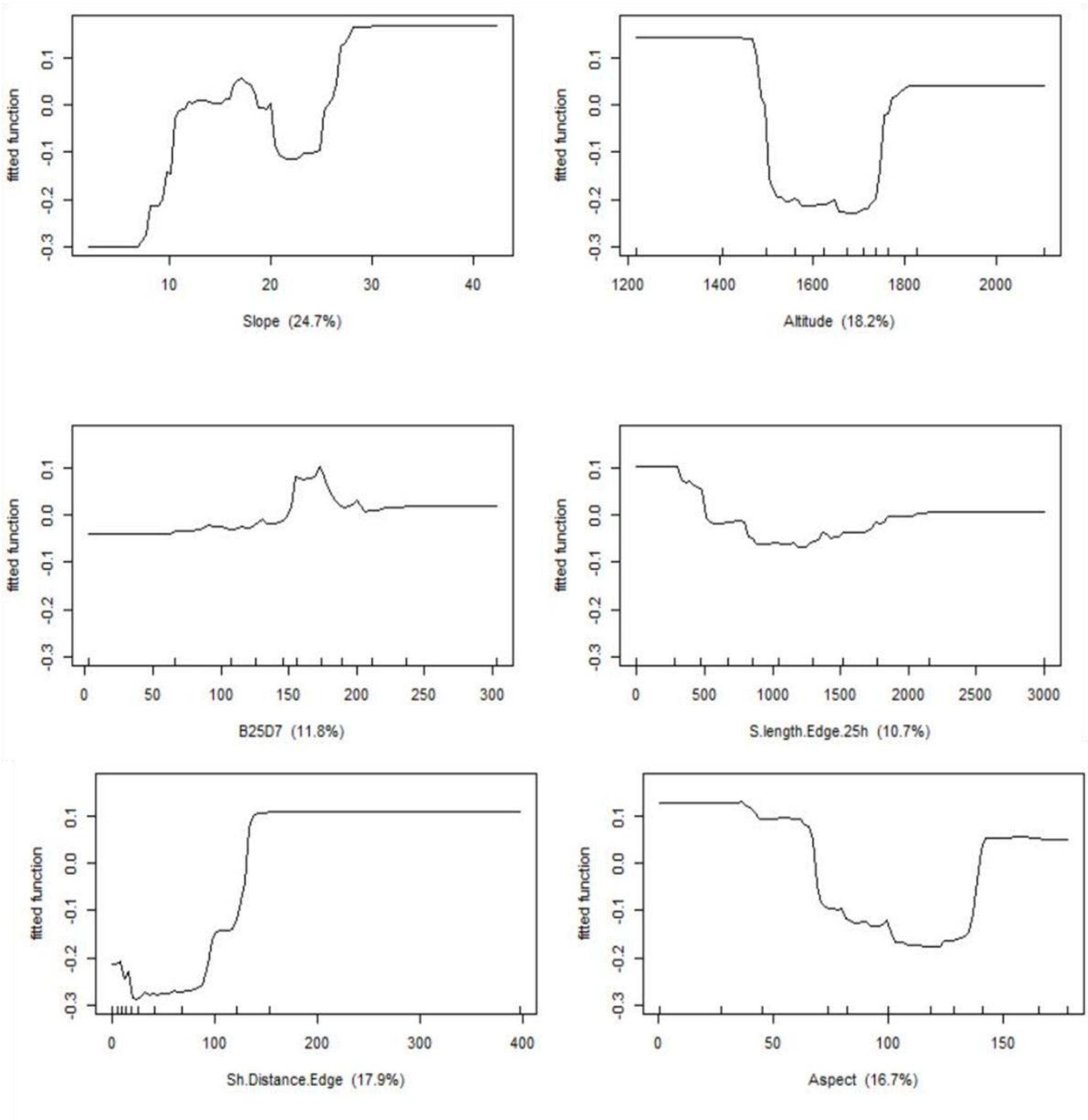
Appendix 8. Internal structure of data set used for fitting models of *G. passerinum* distribution

```
$ ID                    : int  1 2 3 4 5 6 7 8 9 10 ...
 $ Source               : Factor w/ 7 levels "Aegol_Article",..: 6 6 6 6 6 6 6 6 6 6 ...
 $ Observation          : int  1 1 1 1 1 1 1 1 1 1 ...
 $ Altitude             : int  1642 1387 1477 1472 1759 1739 1731 1754 1773 1649 ...
 $ Slope                : num  11.87 8 15.5 19.85 9.81 ...
 $ Aspect               : num  99.9 140.2 166.9 144.1 141.3 ...
 $ Shortest.Distance.Edge  : num  198.58 96.85 121.75 7.36 6.09 ...
 $ Sum.length.Edge.25h : int  858 1706 2185 2297 1523 217 297 1021 771 1355 ...
 $ B25D3                : int  1434 360 926 366 1009 1336 1346 1023 1423 1069 ...
 $ B25D4                : int  919 219 574 227 631 733 723 649 794 640 ...
 $ B25D5                : int  561 136 336 146 406 413 387 389 443 396 ...
 $ B25D6                : int  370 86 223 105 276 249 242 263 265 257 ...
 $ B25D7                : int  243 51 130 80 200 150 153 171 156 172 ...
 $ B25D8                : int  164 34 82 55 144 87 91 112 98 120 ...
 $ B25D9                : int  101 19 55 39 98 55 58 76 62 68 ...
 $ B25D10               : int  71 14 40 29 62 33 38 55 37 39 ...
 $ B25D11               : int  30 7 26 14 34 21 20 34 20 22 ...
 $ B25D12               : int  17 3 12 8 15 10 13 19 9 7 ...
 $ B25D13               : int  4 2 3 3 2 0 4 5 2 3 ...
 $ Sum.length.Edge.50h : int  1345 2774 4277 4817 3706 569 487 2342 1912 2135 ...
 $ B50D3                : int  3176 1002 1591 919 1863 2570 3004 2011 2616 2477 ...
 $ B50D4                : int  1927 584 1000 557 1163 1456 1707 1213 1501 1395 ...
 $ B50D5                : int  1145 340 600 362 752 870 961 757 837 845 ...
 $ B50D6                : int  723 219 391 250 502 528 573 510 514 524 ...
 $ B50D7                : int  471 136 260 179 355 331 371 320 324 341 ...
 $ B50D8                : int  313 82 169 124 252 206 224 208 201 230 ...
 $ B50D9                : int  197 50 113 86 171 135 139 128 137 137 ...
 $ B50D10               : int  128 31 77 60 109 96 85 82 85 77 ...
 $ B50D11               : int  68 16 47 34 60 55 46 45 47 40 ...
 $ B50D12               : int  31 7 21 16 29 29 28 21 17 16 ...
 $ B50D13               : int  4 4 6 5 4 6 9 5 4 6 ...
 $ Sum.length.Edge.100h: int  2067 5054 7887 10350 6534 1662 1433 4110 4809 3473 ...
 $ B100D3               : int  6267 2558 2369 2473 4553 5527 5587 4103 4865 5338 ...
 $ B100D4               : int  3744 1483 1487 1544 2890 3162 3194 2291 2786 2999 ...
 $ B100D5               : int  2172 855 917 966 1835 1862 1802 1330 1593 1736 ...
 $ B100D6               : int  1367 537 607 643 1228 1169 1099 861 1003 1078 ...
 $ B100D7               : int  887 332 415 439 831 720 689 542 640 686 ...
 $ B100D8               : int  563 207 271 283 556 436 431 359 431 438 ...
 $ B100D9               : int  345 136 185 202 384 270 265 229 290 265 ...
 $ B100D10              : int  214 85 127 136 244 181 171 147 173 158 ...
 $ B100D11              : int  115 44 75 79 130 100 95 86 98 88 ...
 $ B100D12              : int  54 21 28 35 61 50 53 39 43 38 ...
 $ B100D13              : int  9 6 7 9 9 9 11 11 9 11 ...
```

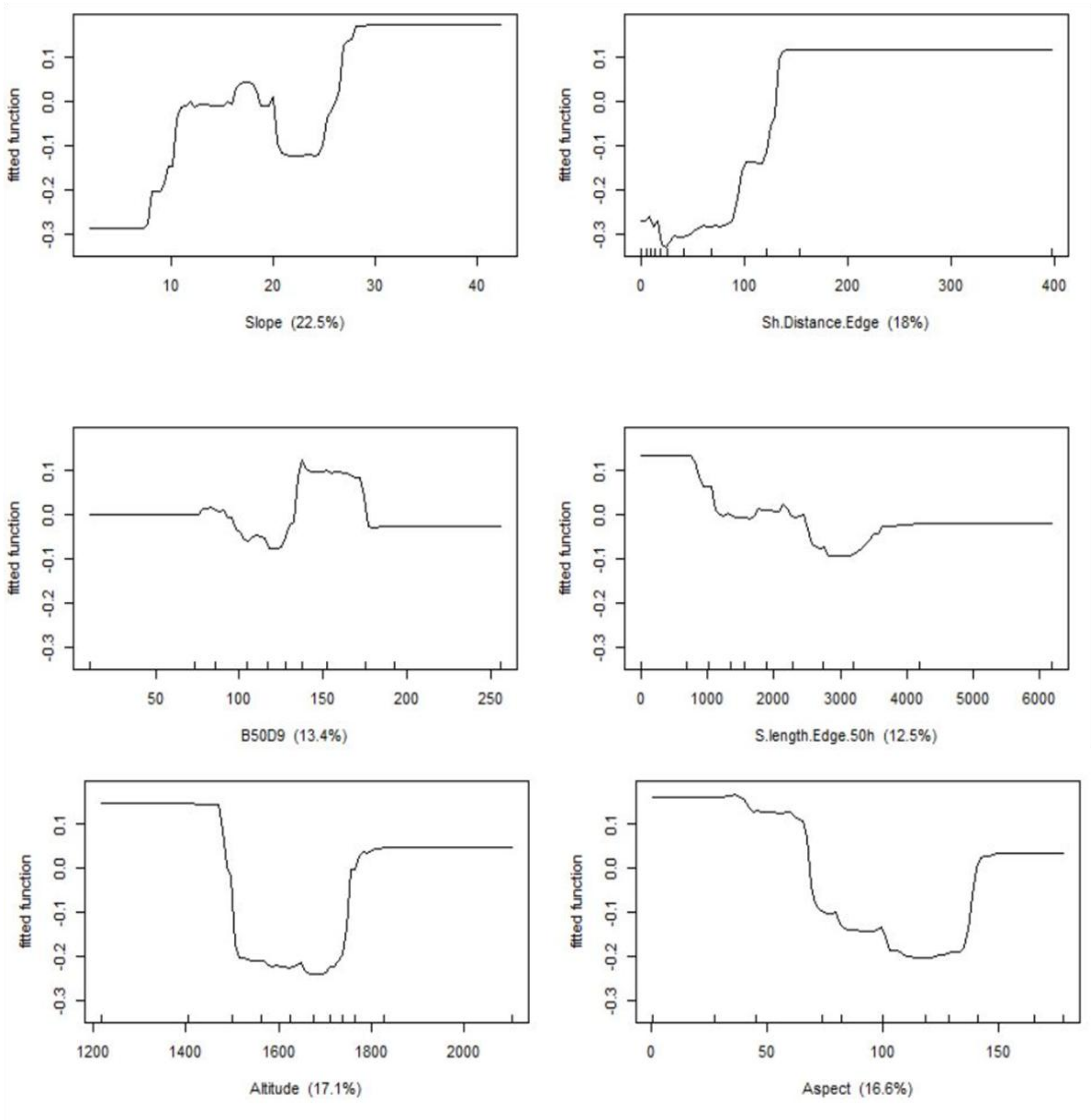
Appendix 9. Internal structure of data set used for fitting models of *A. funereus* distribution

```
$ ID                    : int  1 2 3 4 5 6 7 8 9 10 ...
 $ Source               : Factor w/ 7 levels "Aegol_Article",..: 2 2 2 2 2 2 2 2 2 2 ...
 $ Observation          : int  1 1 1 1 1 1 1 1 1 1 ...
 $ Altitude             : int  1239 1218 1387 1439 2014 2077 2095 2105 1920 1549 ...
 $ Slope                : num  30.9 25 28.5 24.1 16.1 ...
 $ Aspect               : num  96.9 102.8 73.7 74.8 88.2 ...
 $ Shortest.Distance.Edge  : num  118.4 28.5 272.9 270.8 15.7 ...
 $ Sum.length.Edge.25h : int  1731 1770 78 107 1338 1085 770 499 1868 673 ...
 $ B25D3                : int  67 489 261 220 394 451 308 81 1036 1192 ...
 $ B25D4                : int  32 283 143 125 233 260 203 34 592 606 ...
 $ B25D5                : int  16 184 80 74 143 151 129 21 354 324 ...
 $ B25D6                : int  5 99 48 46 85 96 84 11 204 182 ...
 $ B25D7                : int  3 64 26 23 57 53 49 9 125 106 ...
 $ B25D8                : int  3 45 17 16 38 35 30 6 85 54 ...
 $ B25D9                : int  1 30 5 7 25 22 18 3 50 29 ...
 $ B25D10               : int  0 12 3 4 17 18 12 3 31 21 ...
 $ B25D11               : int  0 8 1 0 7 14 8 2 18 11 ...
 $ B25D12               : int  0 4 1 0 6 8 5 0 6 6 ...
 $ B25D13               : int  0 0 1 0 3 0 1 0 1 2 ...
 $ Sum.length.Edge.50h : int  3174 3005 761 576 2813 2082 1681 1141 3241 1634 ...
 $ B50D3                : int  389 806 653 652 1273 1103 670 225 1858 2336 ...
 $ B50D4                : int  207 441 365 398 758 626 406 108 1082 1246 ...
 $ B50D5                : int  125 273 225 256 465 376 250 67 659 693 ...
 $ B50D6                : int  65 160 140 168 283 232 157 39 401 410 ...
 $ B50D7                : int  36 109 80 99 190 148 99 30 261 250 ...
 $ B50D8                : int  23 72 48 62 121 93 64 21 179 153 ...
 $ B50D9                : int  11 48 27 37 75 61 42 13 114 97 ...
 $ B50D10               : int  6 25 19 23 45 42 29 9 77 63 ...
 $ B50D11               : int  4 16 10 11 29 29 17 7 50 30 ...
 $ B50D12               : int  3 10 3 4 13 17 9 2 25 12 ...
 $ B50D13               : int  0 1 1 0 4 3 2 0 5 3 ...
 $ Sum.length.Edge.100h: int  8193 5810 2411 2151 4556 4610 3552 3625 3991 5573 ...
 $ B100D3               : int  970 1308 1720 1562 3744 2213 1858 1284 3458 4223 ...
 $ B100D4               : int  523 726 988 900 2254 1323 1083 713 2091 2324 ...
 $ B100D5               : int  317 444 590 570 1352 799 634 424 1306 1357 ...
 $ B100D6               : int  176 254 353 337 851 505 407 258 839 814 ...
 $ B100D7               : int  114 170 205 211 541 323 259 164 559 518 ...
 $ B100D8               : int  78 108 121 136 351 206 164 111 386 331 ...
 $ B100D9               : int  48 73 76 74 217 133 104 72 258 216 ...
 $ B100D10              : int  26 41 48 47 133 89 68 48 171 144 ...
 $ B100D11              : int  17 29 28 26 74 47 41 32 108 78 ...
 $ B100D12              : int  8 17 8 9 34 29 25 15 57 35 ...
 $ B100D13              : int  2 1 4 4 8 7 4 2 13 9 ...
```

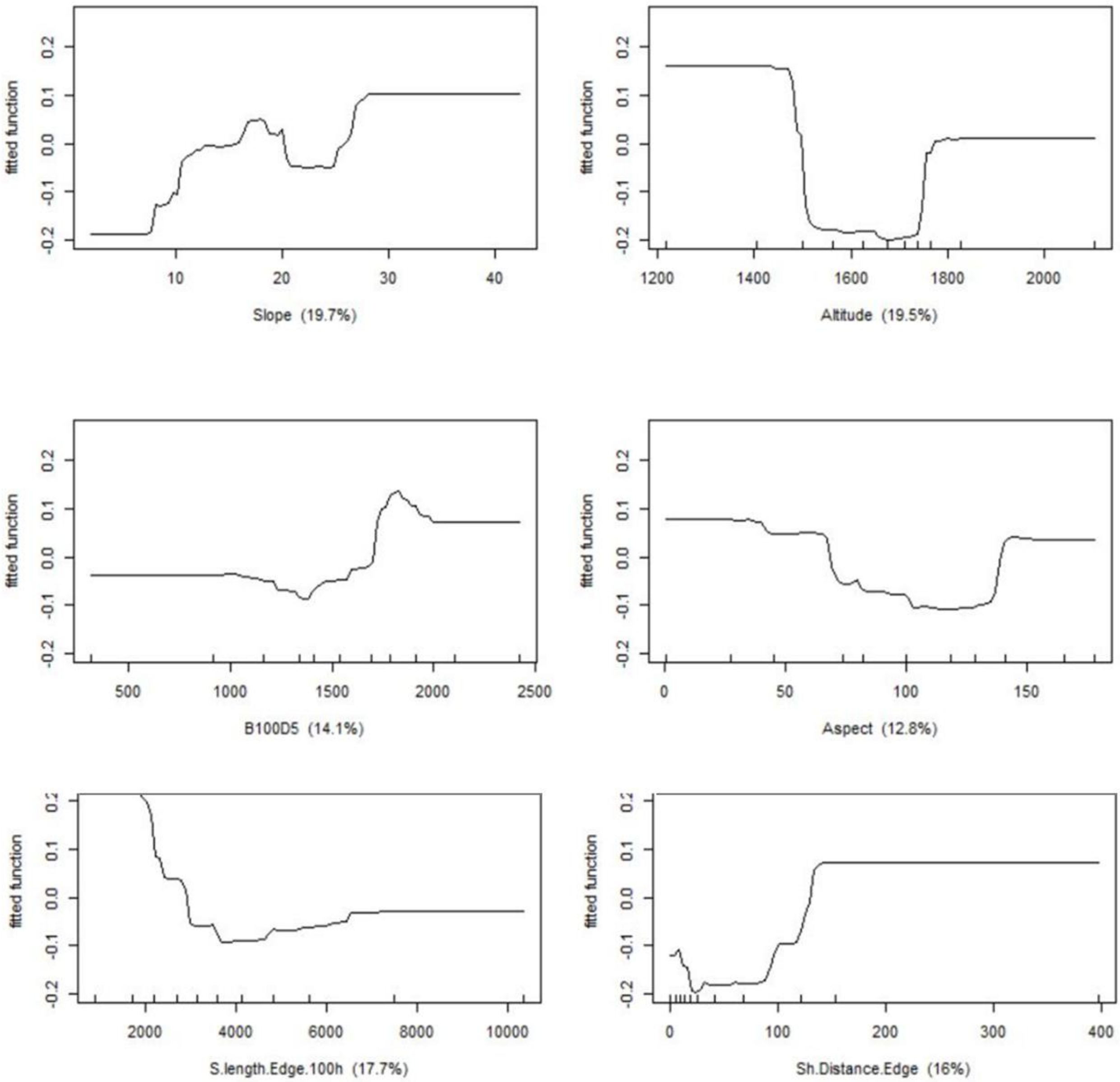
Appendix 10. Partial dependence plots from highest MaxKappa values of BRT models on *G. passerinum* distribution in 25 hectares with y axis on the logit scale



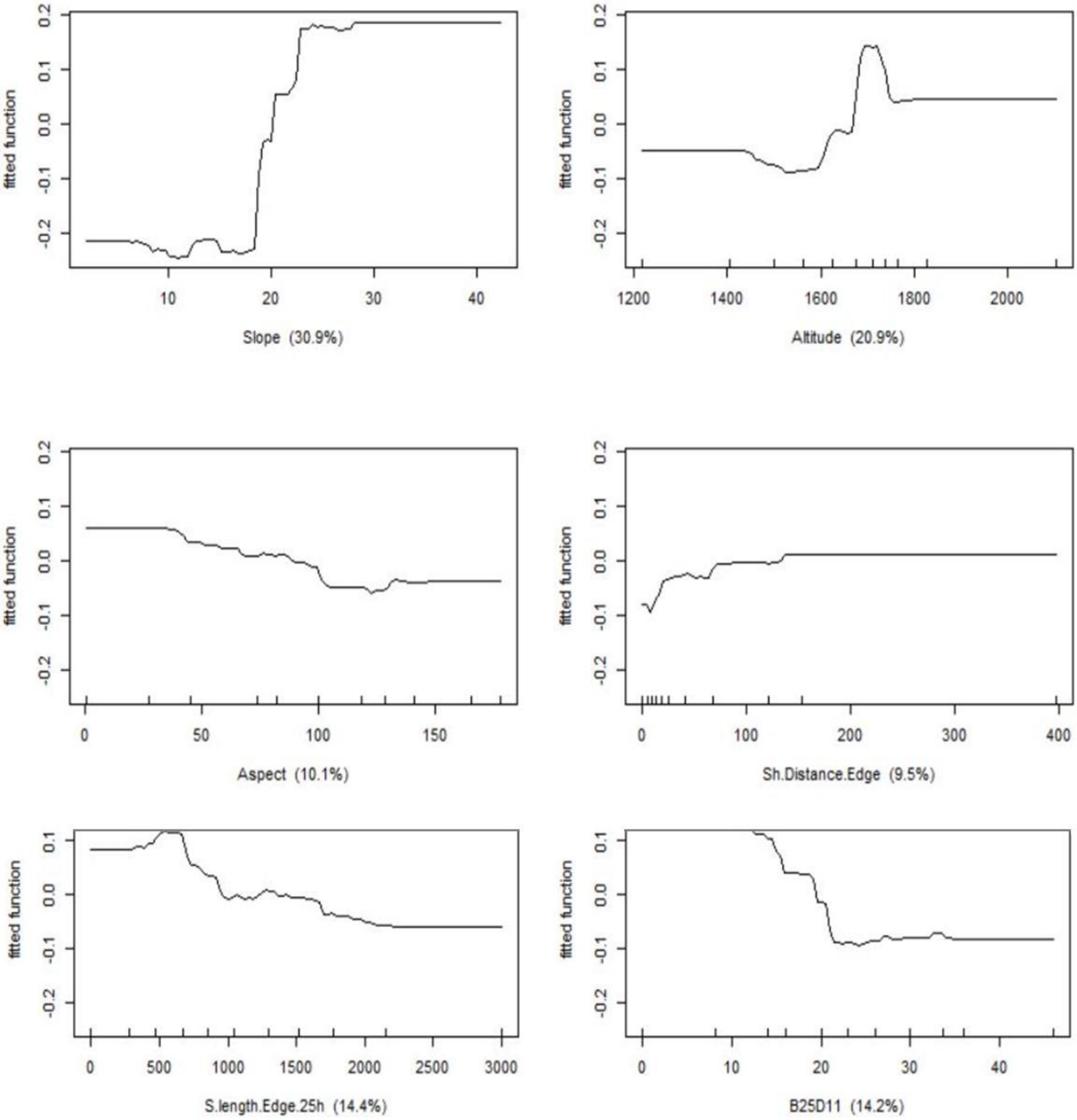
Appendix 11. Partial dependence plots from highest MaxKappa values of BRT models on *G. passerinum* distribution in 50 hectares with y axis on the logit scale–



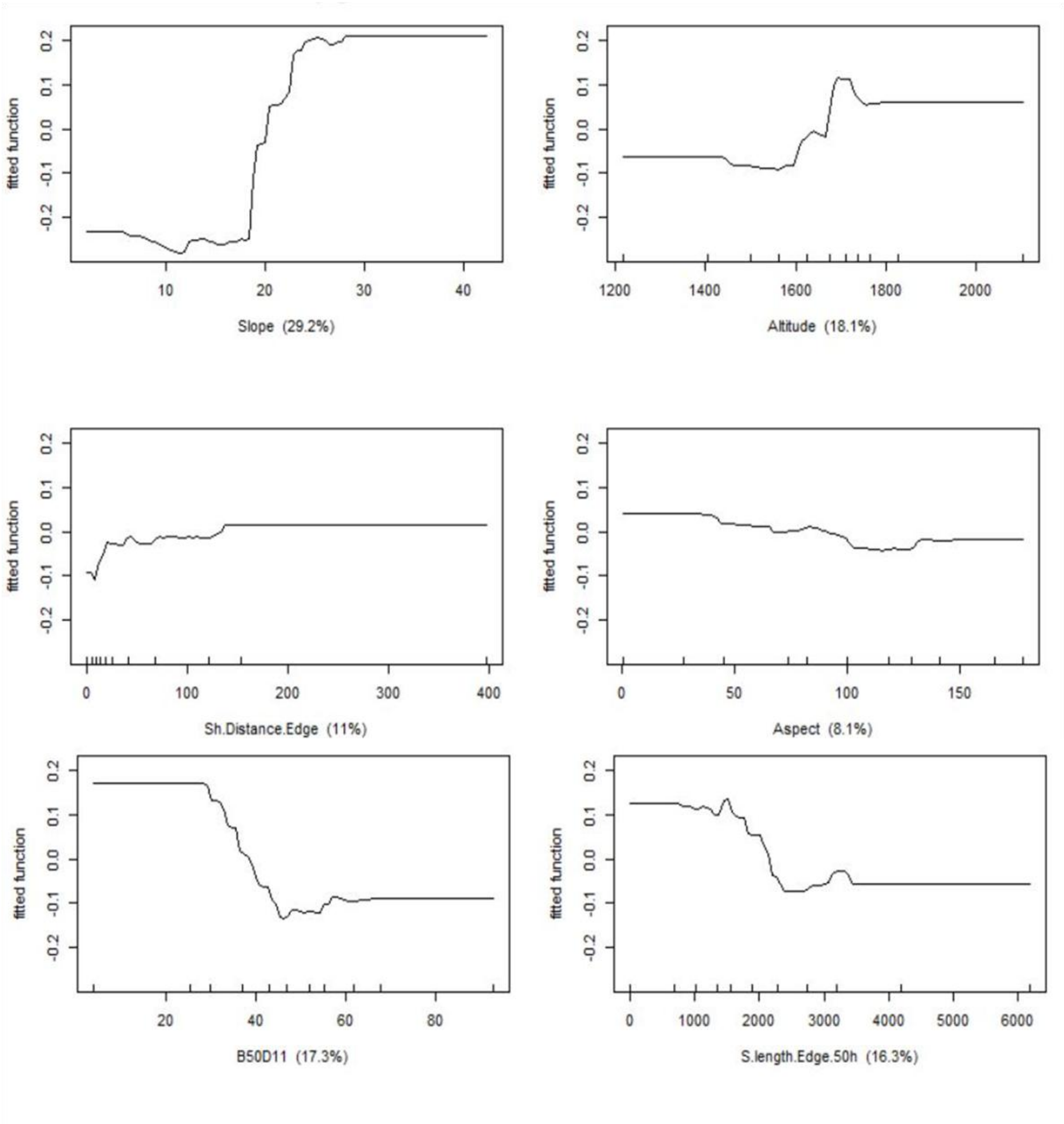
Appendix 12. Partial dependence plots from highest MaxKappa values of BRT models on *G. passerinum* distribution in 100 hectares with y axis on the logit scale–



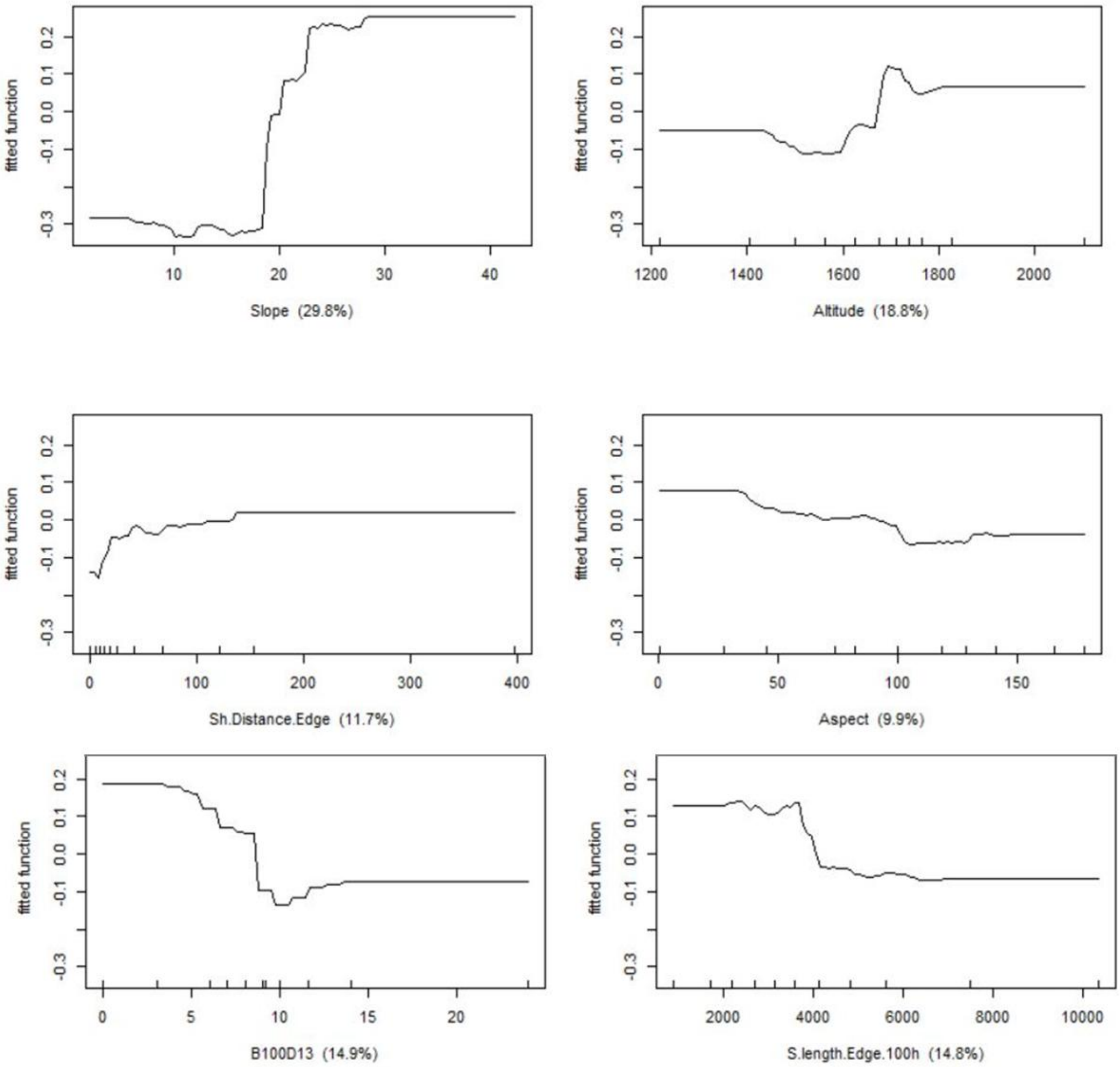
Appendix 13. Partial dependence plots from highest MaxKappa values of BRT models on *A. funereus* distribution in 25 hectares with y axis on the logit scale–



Appendix 14. Partial dependence plots from highest MaxKappa values of BRT models on *A. funereus* distribution in 50 hectares with y axis on the logit scale



Appendix 15. Partial dependence plots from highest MaxKappa values of BRT models on *A. funereus* distribution in 100 hectares with y axis on the logit scale



Appendix 16. Comparison between relative influence of variables from best fitted BRT model with highest MaxKappa values in 25 hectares between *G. passerinum* and *A. funereus*

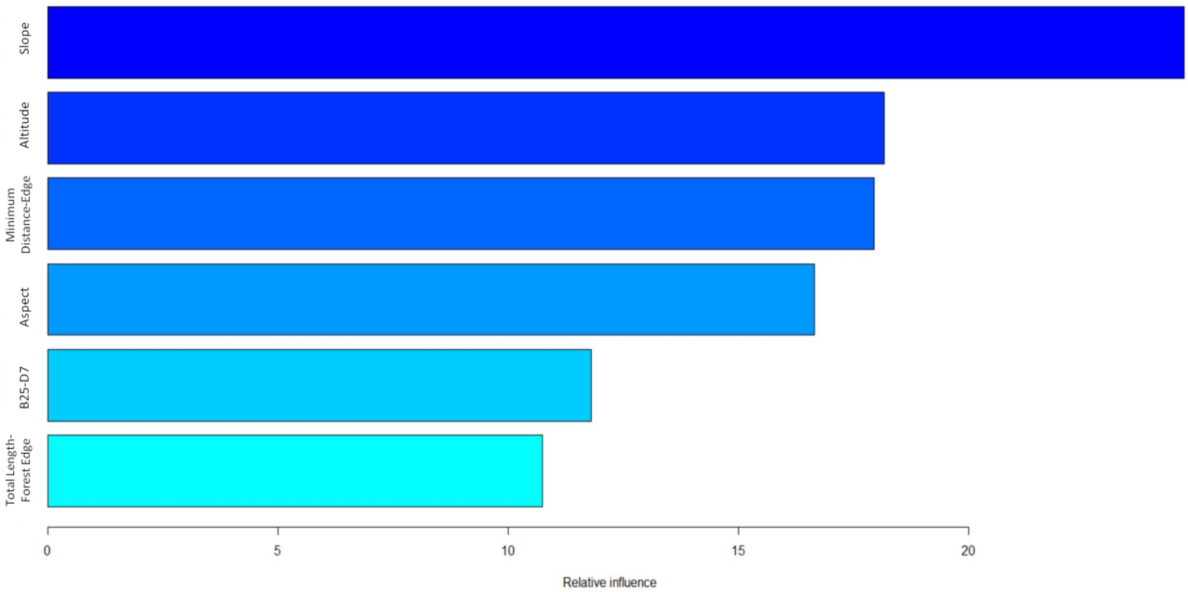


Figure 25. Relative influence of variables from best fitted BRT model for *G. passerinum* in 25 hectares

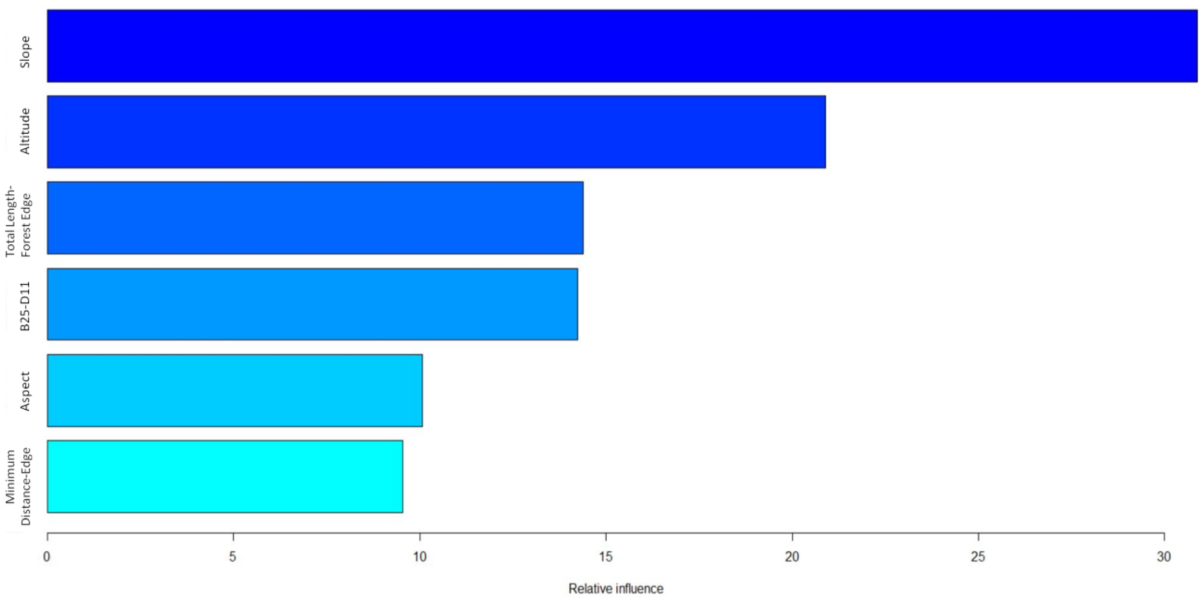


Figure 26. Relative influence of variables from best fitted BRT model for *A. funereus* in 25 hectares

Appendix 17. Comparison between relative influence of variables from beset fitted BRT model with highest MaxKappa values in 50 hectares between *G. passerinum* and *A. funereus*

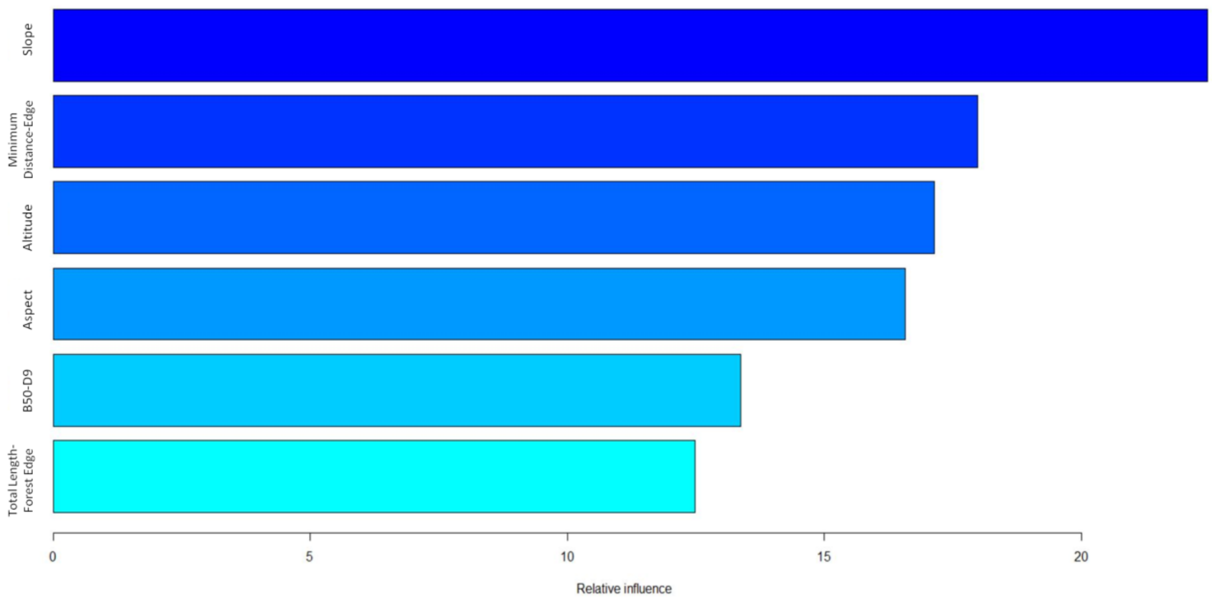


Figure 27. Relative influence of variables from best fitted BRT model for *G. passerinum* in 50 hectares

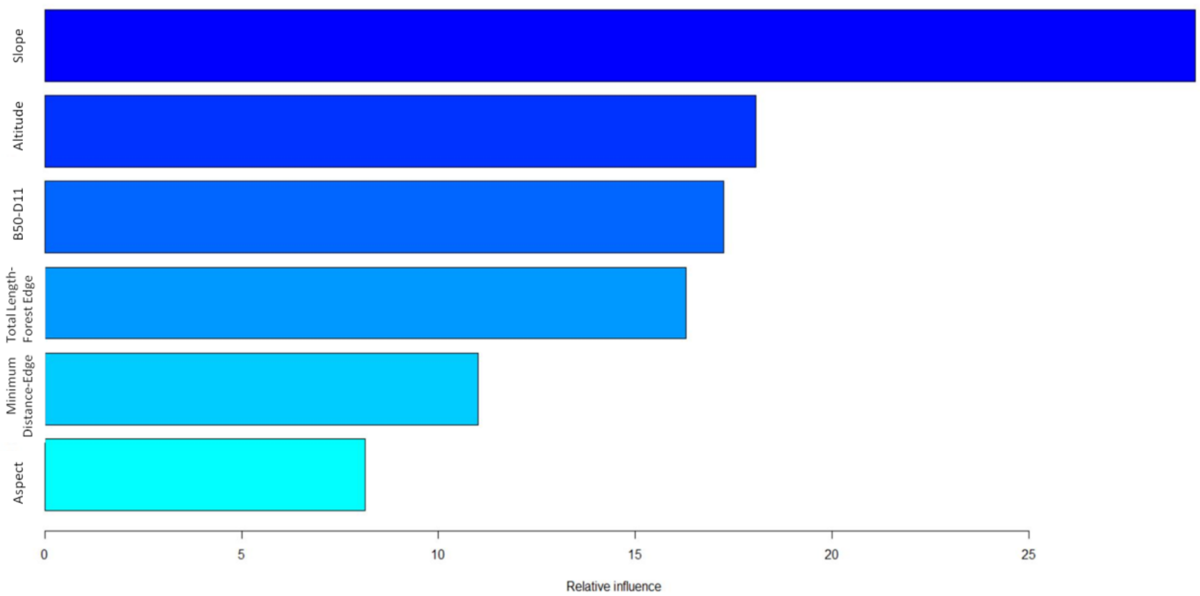


Figure 28. Relative influence of variables from best fitted BRT model for *A. funereus* in 50 hectares

Appendix 18. Comparison between relative influence of variables from beset fitted BRT model with highest MaxKappa values in 100 hectares between *G. passerinum* and *A. funereus*

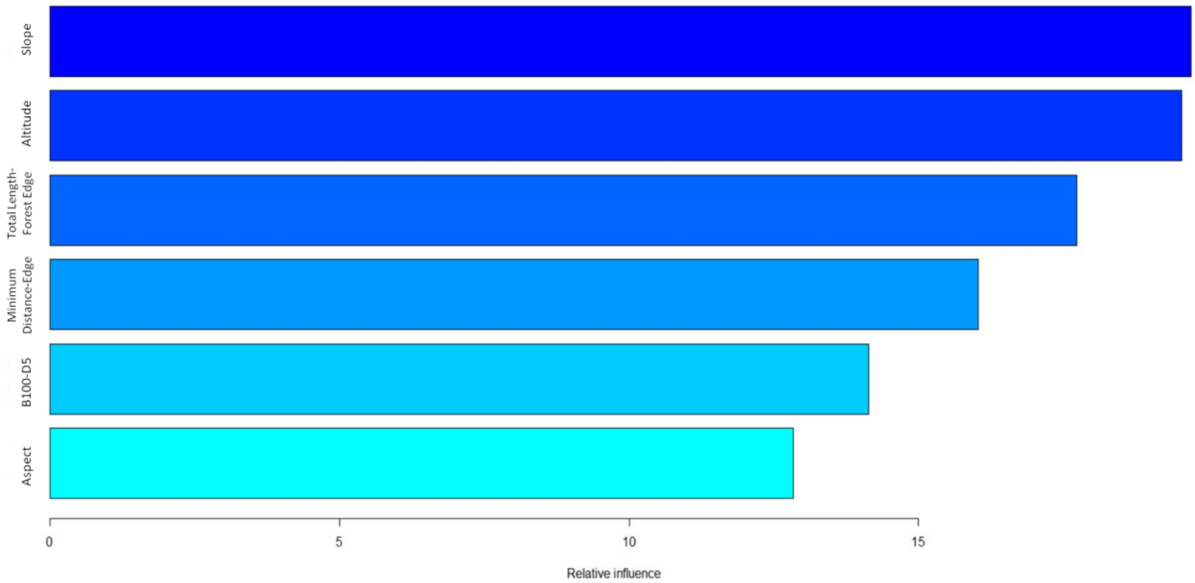


Figure 29. Relative influence of variables from best fitted BRT model for *G. passerinum* in 100 hectares

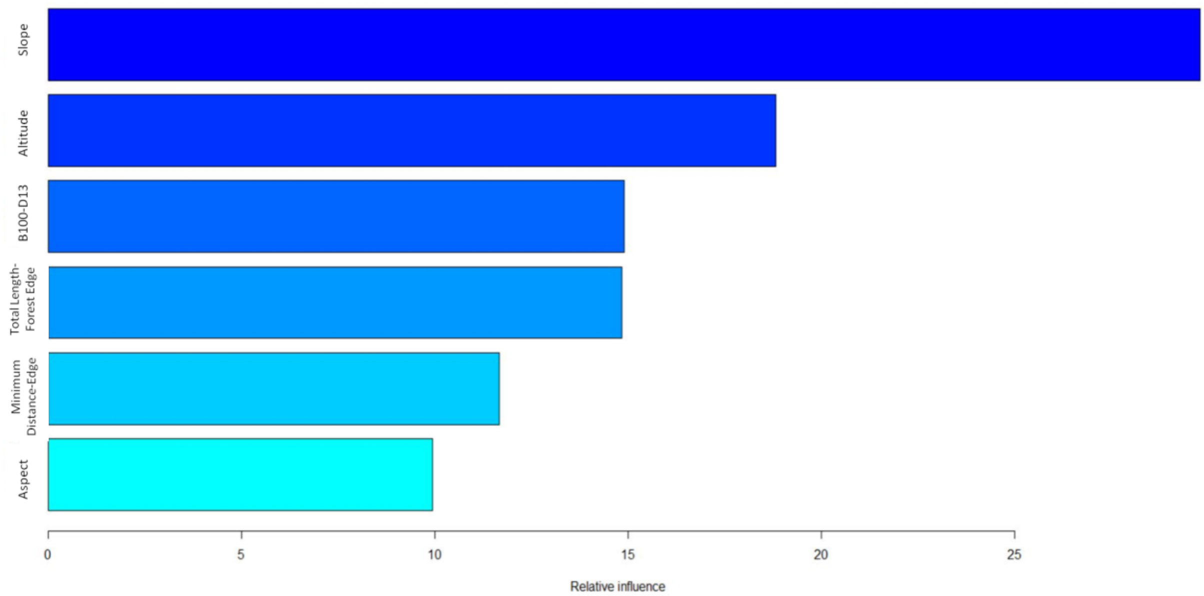


Figure 30. Relative influence of variables from best fitted BRT model for *A. funereus* in 100 hectares