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THE ROLE OF FOREST GROWTH IN HABITAT QUALITY DYNAMICS

Predicting future roe deer habitat using logistic and logarithmic regression

DIE ROLLE DES WALDWACHSTUMS IN DER DYNAMIK DER HABITATQUALITÄT

Die Abschätzung der künftigen Habitatqualität für Rehwild mit Hilfe von logistischen und logarithmischen Regressionsmodellen

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Abstract: Forest management not only changes the vegetative composition of the forest stand but also the composition and dynamics of the understory herb, forb and shrub layers. These changes will effect the use of these stands by roe deer by altering their habitat. One method of determining the effects of forest management is to predict and evaluate future wildlife habitat suitability indices under different management strategies. The objective of this project was to develop empirical understory vegetation models to predict the change of understory vegetation over time. Using the Austrian National Forest Inventory, a hierarchical two model approach was used. First, logistic regression was used to predict the probability of the understory vegetation being present or absent in the future. Then, if the understory vegetation type was predicted to be present in the future, it was quantified using logarithmic regression. This modelling strategy is unique because it models the change in understory vegetation. Also, the strategy uses variables from both the current forest and the future forest (predicted by a growth model). In application, the models developed in this study can be used to evaluate the effects of different management strategies on understory vegetation and roe deer habitat.

Keywords: Roe deer, understory vegetation modeling, habitat suitability indices, logistic regression, Austria.

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Kurzfassung: Forstwirtschaftliche Maßnahmen ändern nicht nur die Dichte und Zusammensetzung der Baumschicht, sondern auch die Strauch-, Kraut- und Grasschicht. Diese wiederum ändern die Habitatqualität für Rehwild. Eine Möglichkeit, die Effekte forstwirtschaftlicher Maßnahmen abzuschätzen besteht darin, künftige Habitatqualitätsindices unter verschiedenen Management-Scenarien modellhaft zu prognostizieren. In der vorliegenden Arbeit werden dynamische, empirische Vegetationsmodelle der Entwicklung der Unterschicht der Waldbestände entwickelt. Mit den Daten der Österreichischen Waldinventur wird ein hierarchischer Modellansatz verwendet. Zunächst wir mittels logistischer Regressionsmodelle die Wahrscheinlichkeit für das künftige Vorahndensein gegebener Vegetationstypen prognostiziert. Im Anschluss daran, wird dann die Mächtigkeit des Vegetationstype mittels log-linearer Regressionsmodelle abgeschätzt. Die besondere Neuheit dieses Modellansatzes besteht in der dynamischen Beschreibung der Veränderung der Vegetation in der Unterschicht der Bestände. Die Eingangsvariablen sind der gegenwärtige und der künftige Zustand der Oberschicht (prognostiziert mittels eines Waldwachstumsmodells). In der Anwendung kann mit den hier entwickelten Modellen der Effekt verschiedener Bestandesbehandlungsmaßnahmen (Durchforstung, Ernte) auf die Bestandesunterschicht und auf die Habitatqualität für Rehwild abgeschätzt werden.

Stichwörter: Rehwild, Habitatqualität, Vegetationsmodelle, logistische Regression, Österreich

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Living and studying in Austria began as a dream,

and ended as an experience

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1 INTRODUCTION

There have been tremendous efforts dedicated to understanding the causes and cures of forest dieback. In Austria, the restoration of monocultured pure Norway spruce stands to their naturally occurring fir-beech mixtures is one of the proposed methods of minimising the effects of forest dieback. These mixed stands are expected to be more resilient to acidic deposition, pollution and climate change while increasing biodiversity. This project is funded by the Special Research Program (SRP) for "Forest Ecosystem Restoration" which is dedicated to researching the many different aspects of forest ecosystem restoration. The proceedings from the "International Conference on Forest Ecosystem Restoration" (2000) is an excellent reference covering many of the diversified subjects concerning forest restoration.

The direct effect of restoration will be seen in the structure of the forest stand. This change will come in the species composition of the regeneration which will be forced upon the site through human intervention (restoration). However their will also be indirect changes within the entire ecosystem. One expected change will occur in the understory herb, forb and shrub layers. There have been many studies which have, for different stand types and conditions, described the understory vegetation changes under different silvicultural systems such as thinning, fertilisation and harvesting (MacLean & Wein 1977; Tappeiner II & Alaback 1989; Reader & Bricker B.D. 1992; Graae & Heskjaer 1997; Elliot et al. 1997; Bailey & Tappeiner 1998; Fredericksen et al. 1999; Thomas et al. 1999). These silvicultural systems can increase the light reaching the forest floor resulting in an increase in the understory vegetation which can translate into an increase in the availability of ungulate browse (Gill et al. 1996). The understory vegetation for ungulates is a source of food and cover (thermal and hiding) (de Jong et al. 1995; Reimoser & Gossow 1996) and any change to these can have a marked effect on the predisposition for use by wildlife. The effects of a particular silvicultural treatment can be viewed both positively and negatively depending on the perspective. Hunters would view clear cuts positively since the harvest of overstory trees would increase the attractiveness of an area to game while increasing visibility. However forest managers, in areas where sufficient regeneration is lacking and the growth rates are slow, would view any increase in attractiveness as a problem (Motta 1996). The negative effects of ungulates on forests is not limited to the browsing regeneration but also includes the fraying of stems and bark peeling (Ammer 1996; Reimoser & Gossow 1996; Motta 1996).

However, Putman (1996) suggested that browsing could also be used positively to aid in increasing forest diversity.

In order to manage any resource sustainability, it is necessary to understand the implications of choosing one management strategy over another. The choice to "restore" forests to their natural mixtures, will have far reaching impacts, one being the effect on ungulates, like roe deer (*Capreolus capreolus).* For ungulates, one aspect of management is to understand its habitat needs. In 1994, Reimoser and Zandl developed Habitat Suitability Indices (HSI) for roe deer in Austria. These indices, for a given moment in time, measure a forest stands predisposition for use by roe deer. One of the key requirements of HSI for an ungulate like roe deer, is the knowledge of the structure of the vegetation (including herb, forb and shrub layers) over time, both at a stand level and on a landscape scale. The difficulty is, how to assess the habitat quality spatially and temporally (Radeloff et al. 1999; Li et al. 2000). The spatial aspects of habitat evaluation have been greatly aided with the development of Geographic Information Systems (GIS) (Garcia & Armbruster 1997; Radeloff et al. 1999; Debeljak et al. 2001). However the temporal aspect is much more difficult. For forests with trees above a minimum breast height diameter, there are numerous individual tree growth models available which can provide information regarding the growth of the trees over time. This provides the wildlife ecologist with a description of the future forest stand, its vertical structure and composition. However, the temporal changes of the understory vegetation, which is essential in predicting future HSI indices, do not exist. In fact, the modelling of the abundance and distribution of understory vegetation has been, comparably, insignificant (Mckenzie & Halpern 1999).

The objective of this study is to address the need for understory vegetation models. These models will predict the change in vegetation over time, more specifically those vegetative parameters, referred to here as HSI parameters, that are needed to calculate the future Habitat Suitability Indices for roe deer developed by Reimoser & Zandl (1994). This will be done with the understanding that a forest growth model can predict, at least a portion of these HSI parameters. Also, the growth model predictions can be used as inputs for the understory vegetation models.

The method chosen to achieve this objective was to build a series of empirical models to predict each of the HSI parameters needed to estimate the future HSI for roe deer. A simple two model approach was used, logistic to predict the probability of a HSI parameter being present or absent in the future, then quantifying it using logarithmic regression. The modelling strategy used has incorporated more information, from both time 1 and time 2 which makes it unique compared to other approaches. This was done to better represent the dynamics of the forest stand and the understory vegetation in predicting future vegetation change.

1.1 Background

In 1985 and 2000, Moeur presented the model "Cover" as an extension to the growth model Prognosis (Stage 1973). There are two major components to "Cover", an option referred to as "Canopy", which controls the prediction of values related to tree crowns, and "Shrubs", which controls the predictions of understory characteristics. The focus of this discussion will be on the "Shrubs" option. The development of "Shrubs" was to assist in, examining the effects of silviculture on forest stand characteristics important to wildlife, and to examine the dynamics of the shrub community affecting stand succession and competition with regeneration.

The "Shrubs" option first predicts the percent total shrub cover by predicting whether or not shrubs will be present or not on the site. This is done using logistic regression. If the shrubs are present, it is quantified using logarithmic regression. Then, the probability of 31 specific species being present or absent on the site is determined using logistic regression. If they are present, the species height and percent cover are determined using logarithmic regression. The model inputs are the same for all models except that in the species models the percent total shrub cover calculated in the first step becomes an input variable. The input variables are slope, aspect, elevation, habitat type, overstory basal area, time since disturbance, type of disturbance, geographic location and topographic position.

The "Shrubs" module of "Cover" is an important work since it is the only modelling framework found where individual understory species are directly predicted in conjunction with a growth model. The significance is that an attempt to make the predictions dependant on dynamic variables, like the overstory basal area, time since disturbance and type of disturbance is made.

Another important facet of "Shrubs" is that the individual species are modelled separately which makes them tremendously flexible in terms of application. However the most important point deals with the two model modelling strategy. Logistic regression is used to predict the probability of occurrence, then the percent cover is quantified using logarithmic regression. This is the methodology that will be used.

The "Shrubs" module of "Cover" however, was based on empirical models that were built from data representing only one moment in time. The only information regarding the dynamics of the forest came from two variables, time since disturbance and type of disturbance. This suggests that no information from time 1, the starting forest condition, was available to the empirical models.

Unfortunately, the shrubs option was never used in application. Maffei et al. (1997), used the model extension "Cover" of the [1]Forest Vegetation Simulator (FVS) to identify northern spotted owl habitat in central Oregon. In this study, owl habitat was classified as either nesting, roosting and foraging habitat, or dispersal habitat. Although both habitat types were of interest, this study focused on dispersal habitat in which the "Shrubs" module of "Cover" was not needed.

The approach that Moeur proposed is the only one that was found that predicted individual understory species directly. There are numerous other examples in the literature, (Davis & DeLain 2000), (Smith 2000), (Benson & Laudenslayer 2000), (Eng 1997), (Brand et al. 2000), where growth models are used to model wildlife habitat, but never by predicting understory vegetation directly. With respect to modelling roe deer, a recent publication by Radeloff et al. (1999) modelled roe deer populations using an interactive geographic information system. Because the study was intended to demonstrate the use of GIS as a tool to spatially model deer populations, the underlying HSI model was very simplistic. A habitat value was the sum of values given by the following parameters; geology, tree composition, the percentage of forest/plowed field boundaries in relation to forest edges and the percentage of grasslands enclosed by forest. Each habitat type was evaluated and a habitat value was classified into poor, medium and good, and assigned a value representing the maximum deer population density for the habitat type. Again, the understory vegetation was not modelled directly.

The Forest Vegetation Simulator (FVS) is an accepted naming convention to encompass all the variants of the Prognosis model

Ignoring the dynamic aspect of understory vegetation for a moment, there are tremendous efforts going into the estimation of current habitat. These models that deal with estimating vegetation habitat are referred to as species response models or environmental gradient models. They predict the probability of the presence or absence of vegetation, as a function of environmental variables (i.e. slope angle, elevation, aspect) and can incorporate current forest cover information (Ertsen et al. 1998; Mckenzie & Halpern 1999). This is similar to the approach that Moeur took, but for different reasons. The primary aim of most species response model studies is to acquire more insight into the spatial distribution of species along environmental gradients (Ertsen et al. 1998). Also, species response modellers are not interested in quantification, their primary interests are the development of maps showing species distribution. There are numerous uses for species response models, for example, they are being used to estimate the habitat range of a given species, predict areas where a given species is most likely to occur or to monitor habitats of rare species. The approach of modelling vegetation habitat can also be applied to modelling wildlife habitat. In 1997, Uygar and Mitsch modelled the spatial habitat for red-winged blackbirds using the same methodology as the species response modellers are using.

The dominant approach in species response modelling is to use a generalised linear model (GLM) with a logistic link function even though there is much discussion concerning its appropriateness (Austin et al. 1984; Huisman et al. 1993; Austin & Gaywood 1994; Oksanen 1997; Bio et al. 1998; Mckenzie & Halpern 1999; Pearce & Ferrier 2000a; Pearce & Ferrier 2000b). Other approaches such as general additive models (GAMs) (Yee & Mitchell 1991) and Canonical Correspondence Analysis (CCA) (Guisan et al. 1999) have been discussed. The GLM approach is not new and has been widely applied in forest and ecological research: in modelling tree mortality (Hamilton 1974; Monserud & Sterba 1999), regeneration recruitment (Schweiger & Sterba 1997) and ingrowth (Ledermann et al. In preparation) and wildlife habitat (Uygar & Mitsch 1997).

From the literature, it is evident that much has been done in predicting future wildlife habitat, however only one attempts to model understory vegetation directly. Moeur's approach is the best attempt at modelling the dynamics of individual species. The prediction of the probability of the presence or absence of the vegetation species is similar to the efforts of the species response modellers. However, so far, the dynamics of the forest stand in species response modelling is not needed and therefore is ignored. In Moeur's work, the forest stand dynamics is only addressed when a human intervention occurs using time since disturbance and type of disturbance to reflect the changes. Normal growth is only addressed using a predicted basal area. Moeur also limits her predictions to stands less than 40 years old. Most importantly, Moeur does not use any information about the shrub species status (presence/absence, %cover, height) from time 1 to predict the future status. It is expected that knowing the status of a species at time 1 will have tremendous impact on its status in the future. Therefore there is also a potential to exploit information about the changes in the forest stand, using information from both time 1 and time 2.

2 MATERIALS

2.1 Austrian National Forest Inventory Data

The Austrian National Forest Inventory (ANFI) (Forstliche Bundesversuchsanstalt 1981,1986 and 1992) was chosen as the modelling dataset. The ANFI meets the requirement that the data must be remeasured on one or more occasions. The ANFI is a continuous forest inventory made up of permanent sample plots (PSPs) that have been remeasured 3 times, 1981, 1986 and 1992. The inventory is a systematic grid of tracts spaced at 3.89 km x 3.89 km, covering all of Austria. At each intersection point, a 200m by 200m square transect is established. At each corner of the transect, 3 types of sample plots are established: 1) a 9.77m ($300m^2$) radius circular plot to collect plot descriptors; 2) a Bitterlich (1948) angle count plot (BAF 4), to select trees above 10.4 cm and 3) a 2.6m ($21m^2$) radius plot to select trees between 5 cm and 10.4 cm. The plots on each corner can be further broken down into up to 4 subplots based on defined administrative, site and stand specific differences within the plot. For this study the subplot is the basis for the modelling process. Figure 2-1 shows the distribution of the subplots used in this study. It should be noted that the subplots are not equal in number and distribution within each of the growth regions. The main problem with ANFI for the current study is that the exact HSI parameters that are needed, do not exist in the inventory, however it was felt that they could be estimated using similar plot descriptors or combinations of several plot descriptors found in the ANFI dataset.

2.2 Response Variables Defined

Of the nine HSI according to Reimoser and Zandl (1994), protection from climate (Klimaschutz Index), protection from enemies (Feindschutz Index), food availability (Nahrungsangebot Index) and habitat (Wohnraum Index), are totally or at least partially based on information from the forest stand and understory vegetation. Table 2-1 presents the 4 HSI and the 14 HSI parameters used to calculate the HSI as well as their description in English and German. The shaded area in the table shows the HSI parameters that can be modelled by a growth model.

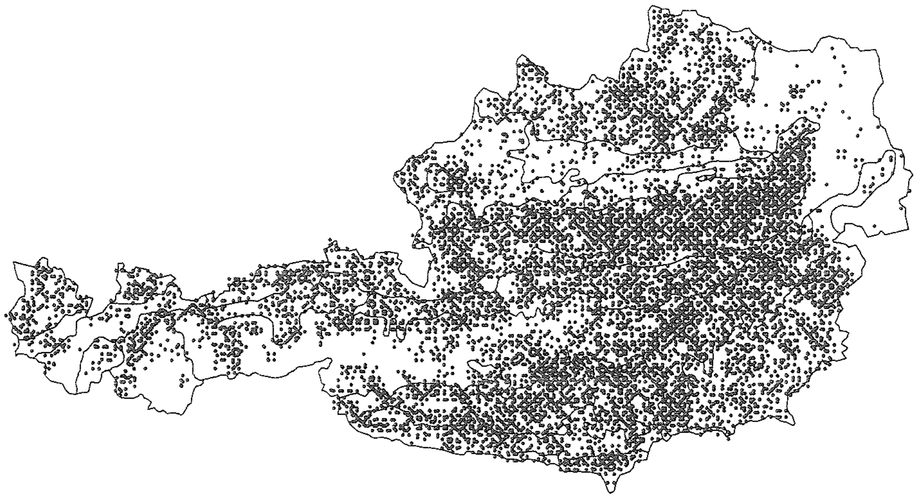


Figure 2-1: Distribution of ANFI subplots used for model development.
Abbildung 2-1: Verteilung der Probeflächen der Österreichischen Waldinventur, die für die Erstellung der Modelle verwendet wurden.

2.2.1 Creating the HSI Parameters from the ANFI Plot Descriptors

The HSI parameters needed were not directly found in the ANFI data. It was therefore necessary to construct the HSI parameters from one or more of the plot descriptors found in the ANFI. These plot descriptors would be individually predicted, then in the final stages combined to represent the needed HSI parameters. The plot descriptors from the ANFI that were of most interest were growth class (Wuchsklasse) and wildlife browse type (Äsungstyp).

Table 2-1: The Habitat Suitability Indices, their associated HSI parameters that must be modelled, and their description in both English and German. Shaded areas represent those HSI parameters that can be modelled by a growth model.

Tabelle 2-1: Die Habitatqualitätsindizes (HSI), die Parameter, die zur ihrer Berechnung modelliert werden müssen und ihre Beschreibung. Grau unterlegt sind alle Parameter, die mit Waldwachstumsmodellen berechnet werden können.

HSI	HSI Parameter	HSI Parameter Description (English)	HSI Parameter Description (German)
Protection From Climate	BESG	Total crown projection area of all plants above 1.3 meters in height (percent)	Beschirmungsgrad gesamt
	GSLH	Total crown projection area of larch above 1.3 meters in height (percent)	Beschirmungsgrad Lärche
	GSLÄ	Total crown projection area of all broadleaved plants above 1.3 meters in height (percent)	Beschirmungsgrad Laubholz
General Living Area	WÖBT	Wildlife Ecological Stand Type (percent)	Wildökologischer Bestandestyp
	050:	Regeneration – for Browse	Äsungsjungwuchs
	060:	Regeneration – for Browse and Cover	Äsung-Deckungs-Jungwuchs
	070:	Regeneration – for Cover	Deckungsjungwuchs
	080:	Thickets	Dickung
	090	Pole	Stangenholz
	100:	Mature	Baumholz
	110:	Advanced Regen under Mature Stand with more than 30% coverage	Fortgeschrittene Verjungung mit Altholzüberschirmung > 30%
	120	Uneven-aged stand	Plenterstruktur
Food Availability	BEGG	Total percent green vegetation below 1.3m	Begrünungsgrad gesamt bis 1.3m
	BEGV	Total percent woody vegetation below 1.3m	Begrünungsgrad verholzte bis 1.3m
	BEVJ	Total percent regeneration below 1.3m	Begrünungsgrad verjungung bis 1.3m
	HEI3	Abundance Blueberry > 30cm (percent)	Abundanz Heidelbeere > 30 cm
	HEI	Abundance Blueberry (percent)	Abundanz Heidelbeere
	GRAE	Abundance Grass (percent)	Abundaz Gräser
	VERH	Abundance of all woody species below 1.3m (percent)	Abundanz einz. Arten verholzte Vegetation bis 1.3m
	VERH3	Abundance of all woody species > 30cm to 1.3m (percent)	Abundanz einz. Arten verholzte Vegetation >30cm bis 1.3m
	ATT1	Abundance of favourite roe deer herbs and grass (percent)	Abundanz vom Rehwild sehr beliebter Kräuter und Gräser
	ATT2	Abundance of moderately favourite roe deer food (percent)	Abundanz vom Rehwild maßig beliebter Kräuter und Gräser
Protection from Enemies	WÖBT	Wildlife Ecological Stand Type (percent)	Wildökologischer Bestandestyp
	050:	Regeneration – for Browse	Äsungsjungwuchs
	060:	Regeneration – for Browse and Cover	Äsung-Deckungs-Jungwuchs
	070:	Regeneration – for Cover	Deckungsjunwuchs
	080:	Thickets	Dickung
	090	Pole	Stangenholz
	100:	Mature	Baumholz
	110:	Advanced Regen under Mature Stand with more than 30% coverage	Fortgeschrittene Verjungung mit Altholzüberschirmung > 30%
	120	Uneven-aged stand	Plenterstruktur

The growth classes represent 8 successional stages of forest cover. Of the 8 growth classes, 6 are of interest in this study (Table A - 2). Each class is assessed in tenths of total area coverage, with the sum totalling 10 or 100%. Any subplot can be assigned up to 5 growth classes. The wildlife browse classes are important indicators of browse availability for ungulates. The wildlife browse classes break the vegetation occurring between the forest floor and 1.5 meters, into 10 classes (Table A - 3). Each class is assessed in tenths of total potential browse with the sum totalling 10 or 100%. It should be noted that areas with "NO BROWSE" are represented as a class. Up to 5 browse classes can be assigned to a given subplot.

In Table 2-2, the ANFI plot descriptors that would be used to represent each of the HSI parameters during the modelling process are shown. Because a two step modelling approach is being used, the response variables take on two forms. For the logistic regression, the response variables are dichotomous (1 or 0), representing the presence or absence of the plot descriptor in the future (i.e. time 2). For quantification modelling, the response variable is formulated as the percent share of the plot descriptor in the future. There are 14 unique plot descriptors, from the two plot descriptor classes, that are needed to predict the HSI parameters Table A - 1. Of these 14, 12 require both a logistic model and a logarithmic model. Two additional logarithmic models are required to quantify the amount of larch and broadleaved trees present in the REGEN II growth class. Logistic models were not needed for these two cases because the presence/absence of REGEN II is made by another model. It should be noted that the growth classes and wildlife browse classes (ANFI) are not measured in the same manner as the HSI parameters. However for this study, it was assumed that they were measured in the same manner.

Table 2-2: The HSI parameters requiring prediction and the ANFI plot descriptors used to model them.

Tabelle 2-2: Die HSI-Parameter, die modelliert werden müssen und die Parameter der Österreichischen Waldinventur, die diese am besten beschreiben.

Vegetative Parameters Requiring Prediction		**Plot Descriptors**	
HSI Parameter	**HSI Parameter Description**	**Growth Class**	**Wildlife Browse Class**
BESG	Total crown projection area of all plants above 1.3 meters in height (percent)	Regen II and larger for all species	
GSLH	Total crown projection area of all broadleaved species above 1.3 meters in height (percent)	Regen II and larger for all broadleaved species	
GSLÄ	Total crown projection area of larch above 1.3 meters in height (percent)	Regen II and larger for stands with larch	
WÖBT	Wildlife Ecological Stand Type (percent)		
050:	Regeneration – for Browse	Regen I	
060:	Regeneration – for Browse and Cover		
070:	Regeneration – for Cover	Regen II	
080:	Thickets		
090	Pole	Pole	
100:	Mature	Mature I and II	
110:	Advanced Regen under Mature Stand with more than 30% coverage	Regen II and Mature I and II	
120	Uneven-aged stand	Regen I and larger for all species	
BEGG	Total percent green vegetation to 1.3m		Sum of all classes except no browse class
BEGV	Total percent woody vegetation to 1.3m		Broadleaved, conifer, shrubs, raspberry, blueberry
BEVJ	Total percent regeneration to 1.3m	Regen I	
HEI3	Abundance Blueberry > 30cm (percent)		Not Available[2]
HEI	Abundance Blueberry (percent)		Blueberry
GRAE	Abundance of Grass (percent)		Grass
VERH	Abundance of all woody species to 1.3m (percent)		Broadleaved, conifer, shrubs, raspberry, blueberry
VERH3	Abundance of all woody species > 30cm to 1.3m (percent)		Not Available[2]
ATT1	Abundance of favourite roe deer herbs and grass (percent)		Not Available[2]
ATT2	Abundance of moderately favourite roe deer food (percent)		Not Available[2]

[2] It was not possible to model these HSI parameters because of a lack of appropriate data. The calculation of the HSI values will be adjusted to accommodate these missing HSI parameters.

2.2.2 Growth Classes

REGEN I

The REGEN I growth class refers to regeneration with an average height less than 1.3 meters. Free standing REGEN I must occupy an area more than $500m^2$. All valid tree species can be considered REGEN I.

REGEN II

The REGEN II growth class refers to regeneration with an average height greater than 1.3 meters and having a diameter at breast height (DBH) of less than 10.4cm. REGEN II can either be free standing or overtopped by another growth class. In both cases REGEN II must occupy an area greater than $500m^2$. All valid tree species can be considered REGEN II. Note: by the design of the inventory, both REGEN I and REGEN II cannot be present in the same plot. If both exist and the $500m^2$ requirement is met, the plot is subdivided into subplots. If this is not possible due to being intermixed, one is chosen over the other.

REGEN II - BROADLEAVED

The REGEN II broadleaved response variable represents the quantity of broadleaved species present in the REGEN II. For this response variable only a logarithmic model is required.

REGEN II - LARCH

The REGEN II Larch response variable represents the quantity of larch species present in the REGEN II. For this response variable only a logarithmic model is required.

2.2.3 Wildlife Browse Classes

NO BROWSE

NO BROWSE refers to total area that has no browsable species or is not browsable. Areas solely made up of moss, birch, alder and some specific herbs and ferns are considered not browsable. Areas with regeneration under a dense pole stand also could be considered unbrowsable. Figure A - 1 illustrates the distribution of the NO BROWSE class compared to the distribution of all the subplots used in the modelling process. The distribution of the subplots with NO BROWSE is evenly distributed within the dataset representing all of the subplots.

CONIFER BROWSE

CONIFER BROWSE refers to the total browsable area that has browsable conifer species such as fir (*Abies* spp.), pine (*Pinus* spp.), spruce (*Picea abies* (L.) KARST) and yew (*Taxus baccata* L.). CONIFER BROWSE does not include dense regeneration that limits access to ungulates. For ungulates such as roe and red deer and chamois, fir (*Abies* alba MILL.) is the preferred conifer species for browse, followed by stone pine (*Pinus cembra* L.), spruce, red *pine (Pinus sylvestris* L.), black pine (*Pinus nigra* ARNOLD) and finally is larch (*Larix decidua* MILL.). With respect to peeling, spruce and fir are preferred followed by stone pine and then the others which are equally desirable (Reimoser and Reimoser 1998). Figure A - 2 illustrates the distribution of the CONIFER BROWSE class compared to the distribution of all the subplots used in the modelling process. The distribution of the subplots with CONIFER BROWSE is evenly distributed within the dataset representing all of the subplots. Interestingly, there are many subplots with CONIFER BROWSE in the primarily deciduous growth zones 9 and 10.

DECIDUOUS BROWSE

DECIDUOUS BROWSE refers to the total browsable area that has browsable deciduous species such as ash (*Fraxinus* spp.), maple (*Acer* spp.), beech (*Fagus sylvatica* L.), hornbeam (*Carpinus betulus* L.), linden (*Tilia* spp.), elm (*Ulmus* spp.), mountain ash (*Sorbus* spp. and Prunus spp.), poplar (*Populus* spp. except black poplar (*Populus nigra* L.)), and chestnut (*Castanea satiava* MILL.). For ungulates such as roe and red deer and chamois, the most desirable browse species are aspen (*Populus tremula* L.), the maples, the *Sorbus* spp., ash, oak, and salix. The next most desirable browse species are the elms, birches, the alders, linden, beech and hornbeam. With respect to peeling, the maples, aspen, elms, ash, hornbeam, beech, salix, mountain ash and wild cherry are desirable. Oak, linden and some *Sorbus* spp. are moderately desirable (Reimoser and Reimoser 1998). Figure A - 3 illustrates the distribution of the DECIDUOUS BROWSE class compared to the distribution of all the subplots used in the modelling process. As expected there are fewer DECIDUOUS BROWSE subplots and their distribution is focused in growth zones 6, 9, 10 and 20, the primarily deciduous regions.

SHRUB BROWSE

SHRUB BROWSE refers to the total browsable area that has browsable shrub species such as elder (*Sambucus* spp.), cornelian cherry (*Cornus mas* L.), haselnut (*Corylus avellana* L.) and, rose (*Rosa* spp.). These species, according to Ellenberg (1996), are half to full light plants, preferring moist to dry sites, never on strongly acid sites, preferring mostly calcareous soils that are moderately to rich in nutrients. Most shrub species are preferred in the diet selection of roe deer (de Jong et al. 1995). Figure A - 4 illustrates the distribution of the SHRUB BROWSE class compared to the distribution of all the subplots used in the modelling process. There are not many SHRUB BROWSE subplots and interestingly their distribution is not in dominant deciduous or coniferous areas such as growth zones 9, 10 and 11, 12 and 13.

RASPBERRY BROWSE

RASPBERRY BROWSE refers to the total area coverage of raspberry *(Rubus idaeus* L.*)*, bromberry (*Rubus* spp.*)* and clematis (*Clematis* spp.). According to Ellenberg (1996) raspberry (*Rubus idaeus* L.*)* is a full light plant, accepting shade up to 30% and prefers nutrient rich soils in lower elevations. Generalising with respect to other *Rubus* spp., they also have similar preferences. *Rubus sp.* are very attractive to roe deer. Figure A - 5 illustrates the distribution of the RASPBERRY BROWSE class compared to the distribution of all the subplots used in the modelling process. The RASPBERRY BROWSE subplots are distributed evenly throughout Austria.

BLUEBERRY BROWSE

BLUEBERRY BROWSE refers to the total area coverage of blueberry (*Vaccinium myrtillus* L.) and lowbush cranberry (*Vaccinum vitis-idaea* L.) According to Ellenberg (1996) blueberry is a 50% shade species preferring wetter, less nutrient rich soils that are more acidic. One characteristic of blueberry sites is the moderately thick layers of humus. Blueberry is very attractive to roe deer. Figure A - 6 illustrates the distribution of the BLUEBERRY BROWSE class compared to the distribution of all the subplots used in the modelling process. The BLUEBERRY BROWSE subplots, as expected, are distributed mostly in the dominantly conifer areas.

ERICA BROWSE

ERICA BROWSE refers to the total area coverage of grey heath (*Erica* spp.) and heather (*Calluna* spp.*)*. According to Ellenberg (1996) *Erica* spp. are all half light plants preferring warmer temperatures. They also prefer acidic soils that are poor in nutrients. *Erica* spp. are not attractive to roe deer. Figure A - 7 illustrates the distribution of the ERICA BROWSE class compared to the distribution of all the subplots used in the modelling process. There are not many ERICA BROWSE subplots and as expected, they are focused in small pockets where the site conditions are suitable.

HERB BROWSE

HERB BROWSE refers to the total area coverage of herbaceous species. According to Ellenberg (1996) the key herbs species have a wide range of site preferences. Most herbs are at least moderately attractive to roe deer. Figure A - 8 illustrates the distribution of the HERB BROWSE class compared to the distribution of all the subplots used in the modelling process. Interestingly, although there are many HERB BROWSE subplots found throughout Austria, HERB BROWSE is concentrated in the predominantly deciduous growth zones 9 and 10.

FERN BROWSE

FERN BROWSE refers to the total area coverage of fern species. The fern species prefer different sites, for example, *Athyrium filix-femina* L. is a shade plant, preferring less than 5% full sunlight. It prefers sites that are wet and high in nutrients with the pH-level being unimportant. *Dryopteris carthusiana* VILL. is a half shade plant, meaning it requires more than 10% full light. It has no preference for soil moisture, but prefers soils that are more acidic and poor in nutrients. *Gymnocarpium dryopteris* L. is a half light plant meaning it prefers less than 30% shade. It prefers wet sites that are basic and poor in nutrients. Certain ferns are attractive to roe deer. Brachen fern (*Pteridium aquilinium* L.) is not considered browse and is classified as NO BROWSE. Figure A - 9 illustrates the distribution of the FERN BROWSE class compared to the distribution of all the subplots used in the modelling process. The FERN BROWSE subplots are found in pockets throughout Austria.

GRASS BROWSE

GRASS BROWSE refers to the total area coverage of the many forest grasses. For roe deer forest grasses are only palatable for short periods during the growing season. Figure A - 10 illustrates the distribution of the Grass BROWSE class compared to the distribution of all the subplots used in the modelling process. The Grass BROWSE subplots are found evenly throughout Austria.

2.3 Explanatory Variables Defined

Available explanatory variables that could potentially influence: a) the likelihood of the response variable being present or absent in the future; or b) the quantity of the response variable that will be present in the future, were to be tested. The ANFI dataset is very comprehensive, offering a wide range of explanatory variables, some of which have measurements from both time 1 and time 2. Because of the complexity of the data, the naming conventions for variables became critical. The following description of the explanatory variables includes the variable name that was used in the modelling process. In the tables this will be clear, however for descriptions of the variable without a table, the variable name will appear in brackets immediately after the name. This should aid in understanding the variable and their estimated coefficients in the results section.

There were 3 types of explanatory variables tested, continuous, discrete and qualitative. For each subplot the explanatory variables modelled as continuous were: elevation (*ELEV*), measured to the nearest 100m; slope (*SLPE*), measured to the nearest 10%; growth class (Table A - 2), measured to the nearest 10% area coverage; wildlife browse class (Table A - 3) measured to the nearest 10% potential browse between the forest floor and 1.5 m; soil moisture (*WTRG*) was ordinally scaled from 1 to 5. For each of the subplots the following forest stand descriptors were calculated and modelled as continuous; basal area (m^2/ha) time 1(*BA_T1*), time 2 (*BA_T2*) and change in basal area (*C_BA = BA_T2 – BA_T1*); quadratic mean diameter (cm) time 1 (*QMD_T1*), time 2 (*QMD_T2*) and change in quadratic mean diameter (*C_QMD = QMD_T2 – QMD_T1*); crown competition factor (Krajicek et al. 1961) time 1 (*CCF_T1*), time 2 (*CCF_T2*) and change in crown competition factor (*C_CCF = CCF_T2 – CCF_T1*) were calculated using open grown crown widths given by Hasenauer (1997); stand density index (Reineke 1933) time 1 (*SDI_T1*), time 2 (*SDI_T2*) and change in stand density index (*C_SDI = SDI_T2 – SDI_T1*). Interval value (*INTVAL*) represents the time between remeasurements, either 5 or 6. This was included to determine if the different remeasurement intervals had a significant effect.

The following qualitative variables were modelled as dichotomous (0 - 1) dummy variables where 1 indicates the presence and 0 indicates the absence of the variable; stand type class time 1 and time 2 (Table A - 4), aspect (Table A - 5), relief (Table A - 6), stand structure at time 2

(Table A - 8), soil types (Table A - 9), ground vegetation type (Table A - 7) and growth zone (Table A - 10) and (Figure A - 11) .

3 METHODS AND MODEL DEVELOPMENT

3.1 Overall Modelling Methodology

3.1.1 Preparation of the Modelling Dataset

The dataset used to model the probability of change in the response variable and to quantify the magnitude of that change, needed to be paired, such that they represent two points in time. Subplots from 1981 were paired with matching 1986 subplots, 5 year re-measurement interval and subplots from 1986 were paired with those in 1992, 6 year re-measurement interval (Figure 3-1). The two datasets were then appended to one another to obtain the modelling dataset. Because there have been notable changes in the data collected, the nomenclature and the measurement scale of parameters between the 3 re-measurements, it was necessary, in some cases, to re-code the data to ensure consistency between re-measurements.

Because the number of subplots between re-measurements can change, only plots where the number of subplots within a plot did not change between remeasurements were used in the analysis. The use of the subplot for the analysis also complicated the calculation of stand parameters since it was necessary to split the angle count into subplots and calculate the per hectare value of stand parameters based on the subplot area rather than the entire plot area. This task was carried out by the Forstliche Bundesversuchsanstalt.

Although all of Austria is covered by this inventory, only subplots defined as: managed forested area, a brush area in a forested area or a protection forest with yield were used for the modelling process. These forest management types were selected because they represent areas where traditional forest management is practised. In the protection forest, a no management objective is considered a management type. Subplots with no tree data, such that no trees were in the angle count, were kept, if the forest management type was present and the subplot was assigned a valid development stage. Any subplots with missing subplot site descriptors were deleted.

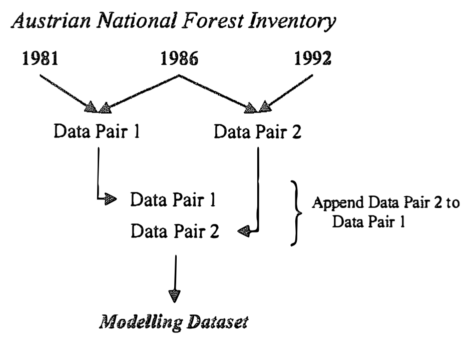


Figure 3-1: Methodology used in building modelling dataset from ANFI.
Abbildung 3-1: Die Entwicklung des Modellierungsdatensatzes aus den Originaldaten der Österreichischen Waldinventur.

The decision to use the subplot for the modelling resulted in a number of concerns. The first concern was whether it was appropriate to consider subplots as independent. Under the inventory specifications, the decision to split a plot into subplots is based on defined criteria at the time of measurement, indicating that there were significant differences between the subplots. This is not unexpected given the small stand sizes and therefore subplots can be assumed to be independent.

Another concern was the estimation of per hectare values for some of the stand parameters. For example, if a plot was subdivided into two subplots, one representing 90% of the area and the other 10%. Under normal circumstances, in considering ingrowth or ongrowth, any new tree coming into a plot would represent 4 square meters of basal area per hectare (assuming a basal area factor of 4). Under the scenario of a subplot representing 10% of the total plot area, a single tree entering this subplot would actually contribute 40 square meters of basal per hectare. Hence, the change in basal area between time 1 and time 2 would be an increase in basal area of 40 square meters. For this reason, some subplots did show very high change in basal area, up to 160 square meters per hectare. Although these types of results were found, they were not removed from the analysis because it was felt that the dataset was large enough that the influence of a single observation would have little influence in the model fit. This was tested and found to be true.

In order to account for the different re-measurement intervals, a variable (*INTVAL*) defining a 5 or 6 year measurement interval was tested during the modelling process to determine if the interval length brought a significant bias.

The final dataset used for the modelling process was made up of 18,076 subplots.

3.1.2 Modelling Strategy

The modelling strategy is hierarchical in structure, using two types of models, a probabilistic model to determine the probability of the response variable being present or absent in the future and a logarithmic regression model that, based on the result of the probabilistic model, quantifies to what degree the response variable will be present. Logistic regression was used for modelling the probabilities and will be discussed in section (3.2). Linear regression with a log transformation of the response variable was used to estimate the quantities and will be discussed in section (3.3).

The justification for using both a logistic and a logarithmic regression model versus a single linear regression model, where the quantity of the response variable would be directly predicted from the entire dataset, is based on the expected performance. The response variable in a logistic model is dichotomous, 0 if in the future the growth class or browse class are not present and 1 if they are present. The logistic models purpose, therefore, is simply to choose which variables discriminate, a future response of 0 or 1, the „best“. In essence the simple 0, 1 response variable is like stratification, thus it was expected that a reasonably good model could be found that differentiated these two cases. The logarithmic model is only needed when the logistic model has determined that in the future there would be a growth or browse class. Thus, the quantification model can be developed on a reduced dataset, one in which all the observations where, no growth class and no browse class present at time 2 have been deleted. This reduced dataset, was expected to also yield a much better fit than a model that was developed based on the entire dataset. In other words, it was believed that two models developed on the stratified and reduced data would perform much better than one model developed on the entire dataset.

The input data set for the logistic models was the modelling dataset as described in section (3.1.1). In order to separate the data into more logical transitional groups and to deal with inherent deficiencies within the data, the data was stratified into several smaller datasets Figure 3-2. For the logistic modelling of the wildlife browse classes, the data was split into two sub-classes based on whether the browse class was present at time 1 or not. The splitting of the data into sub-classes was done for two reasons. The first was to differentiate what transitional progression was being modelled. For example, if the browse class is present at time 1, the factors which determine whether or not the class stays on a site, or disappears, are significantly different than those, when the browse class is not present at time 1 and encroaches onto a site. The second reason was, when the data was not split, it was very difficult to obtain a good fit with logistic regression. Furthermore, there were many interactions between covariates, thus making the coefficients very difficult to interpret. It was felt that two logistic models with better fits that were simpler and more interpretable were a better choice.

In the logistic modelling of the regeneration classes, the data was also split into two sub-classes based on whether the regeneration class was present at time 1 or not. The reasons were the same as for the wildlife browse classes. However, these two sub-classes were split again based on whether there were trees (greater than 5.0 cm) present in the plot at time 1. The reason for splitting the data into „with trees“ at time 1 and „without trees“ at time 1 was based on the ANFI data. Some stand parameters, such as crown competition factor (CCF), stand density index (SDI) and basal area (BA) are calculated only from those trees above 5.0 cm, suggesting for example, that a stand of REGEN I has no CCF, SDI and BA, which is definitely not the case and would erroneously affect the model. By splitting the data, advantage could be taken of BA, SDI and CCF when there are trees and could be ignored in the analysis when they are not appropriate. In Figure 3-2 the response variables have been updated to reflect the case that is being modelled. The "- 1" after the name refers to present at time 1 and "- 0" refers to not present at time 1. The "with trees" and "without trees" refer to the status of the overstory at time 1.

Once the logistic models were complete, began modelling to quantify the growth classes and the wildlife browse classes began. The input dataset for the linear regression modelling was a stratified dataset, where only the observations that were *„correctly predicted"* by the logistic model were used. There are two factors that must be mentioned at this point. Firstly, there was the option to stratify the input dataset differently, in a way that only observations, where the percent share of the response variable at time 2 was greater than 0, were used. After some testing, it was found that the dataset that used the „correctly predicted values" consistently fit better with higher R^2 values. The second factor that should be mentioned deals with cutoff values. The selection of the correctly predicted observations from logistic regression, is based on a threshold or cutoff probability. It was not initially clear what the most appropriate cutoff point should be. In order to aid in selecting the most appropriate cutoff point, the logistic model performance was tested using different cutoff points. It was determined that the a priori probability, (the ratio of the number of observations with a response of 1 at time 2 over the total number of observations), was the most appropriate. The results and a detailed discussion regarding the development of the input dataset for the logarithmic models and the selection of the most appropriate cutoff point are presented in section (3.4).

Once the probabilistic and quantity modelling was complete, an overall performance evaluation of the two model strategy was carried out. Unfortunately, this was not done on an independent dataset so it could not be considered a true validation process. A more detailed explanation of the evaluation is presented in section (3.5).

3.1.2.1 Cases where no models were fit

From Figure 3-2 it can be seen that there were 5 cases where no models were fit, red crosses. The main reason was that there were insufficient observations to fit a model. However, it is still necessary to represent these events in application, even though they are not frequently observed. In the results section (0), a proposed method to represent each of the cases in application is presented.

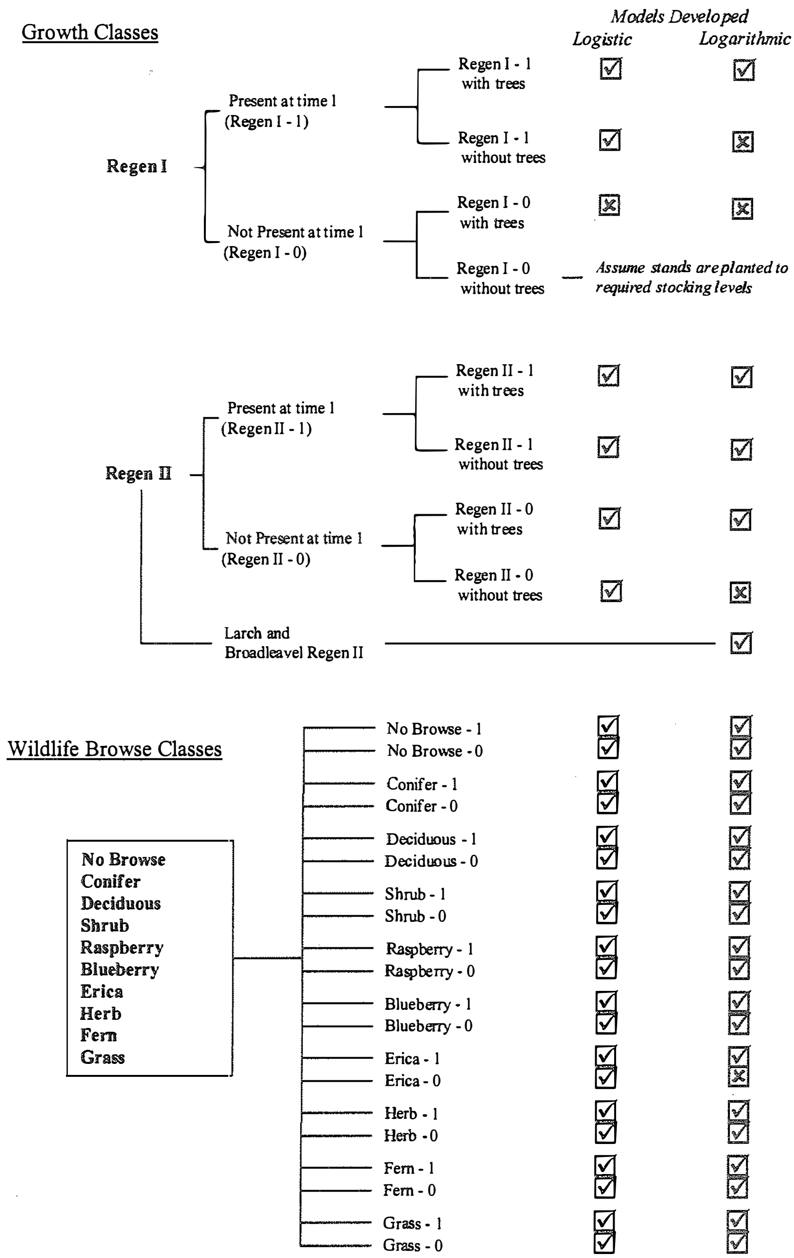


Figure 3-2: The modelling strategy; where the check marks indicate a model was fit and the crosses indicate that a model could not be fit. For the cross cases, alternative methods for making future prediction are presented in the results section.

Abbildung 3-2: Die Modelle. Ein grüner Hacken bedeutet, dass ein Modell angepasst werden konnte, eins Kreuz bedeutet, dass kein Modell angepasst werden konnte. In diesen Fällen werden alternative Methoden der Schätzung im Ergebnisteil vorgestellt.

3.2 Logistic Regression

3.2.1 Model Specifications

Let Y denote a dichotomous (0,1) response variable and x denote a value of an independent variable. The expected value of Y given x, is the conditional mean and expressed as $E(Y|x)$. If we denote $\pi(x)$ as the probability of a species being present (Y=1) in the future for a given x, then the $E(Y|x)$ is $p = probability(Y=1|x) = \pi(x)$. Because the response variable is dichotomous, it is limited by the fact that $\pi(x)$ must be greater than or equal to zero and less than or equal to 1 ($0 \leq E(Y|x) \leq 1$). In order to meet this limitation, the characteristic s-shaped logistic distribution was chosen, represented by the logistic cumulative distribution function:

$$p = \pi(x) = \frac{1}{1+\exp^{-(\beta_0 + x_1\beta_1 + x_2\beta_2 ... + x_k\beta_k)}} = \frac{\exp^{(\beta_0 + x_1\beta_1 + x_2\beta_2 ... + x_k\beta_k)}}{1+\exp^{(\beta_0 + x_1\beta_1 + x_2\beta_2 ... + x_k\beta_k)}}.$$

The concept of linear regression is based on the assumption that $E(Y|x)$ can be expressed as a linear combination in x,

$$E(Y \mid x) = \beta_0 + x_1\beta_1 + x_2\beta_2 ... + x_k\beta_k$$

With the logistic function this assumption cannot be met. However, by using the generalised linear model (McCullagh and Nedler, 1983), the model above can be re-expressed as

$$g(p) = g(\pi(x)) = \beta_0 + x_1\beta_1 + x_2\beta_2 ... + x_k\beta_k$$

where g(.) is a link function which relates the probability of the presence of a species with the linear combination of the variables. The logistic link function

$$g(p) = g(\pi(x)) = \log\left[\frac{\pi(x)}{1-\pi(x)}\right] = \beta_0 + x_1\beta_1 + x_2\beta_2 ... + x_k\beta_k$$

is linear in its parameters and expands the 0 to 1 interval of the response variable to a $-\infty$ to ∞ interval (Bio et al. 1998). The transformation of p is referred to as the logit transformation with the $g(p)$ term referred to as the logit.

In addition to the logistic link, the other two commonly used link functions are the probit link, which models the normal cumulative distribution function and compliment log-log link which models the extreme-value distribution function. The logistic model was chosen for this study because it is the most commonly used link function for dichotomous variables (Yee & Mitchell, 1991; Huisman et al., 1993).

3.2.2 Maximum Likelihood Estimation

Under linear regression, the unknown parameters $\beta_0, \beta_1 \ldots \beta_k$ are estimated using least squares methods. However, when the response variable is dichotomous, the desirable properties of these parameters, (unbiased, normally distributed and with a minimum variance among the parameters) are no longer the valid. In these cases the method of maximum likelihood estimation is used. This method yields estimates of the unknown regression parameters by maximising the probability of obtaining the observed set of data (Hosmer & Lemeshow, 2000, p.8).

The basic concept is as follows. When the dichotomous response variable Y = 1 , then $p = probability(Y=1|x) = \pi(x)$. Conversely, when the dichotomous response variable Y = 0 , then $p = probability(Y=0|x) = 1 - \pi(x)$. If y_i represents the response variable for the i-th observation and x_i the vector of explanatory variables for the i-th observation, then the contribution by each (y_i,x_i) pair in the search for the maximum probability is determined using the expression

$$\pi(x_i)^{y_i}\left[1-\pi(x_i)\right]^{1-y_i}.$$

The maximum likelihood function is the product of each individual contribution of (y_i,x_i) expressed as follows:

$$l(\beta) = \prod_{i=1}^{n} \pi(x_i)^{y_i}\left[1-\pi(x_i)\right]^{1-y_i} \tag{4.1}$$

where $\beta = (\beta_0, \beta_1 \ldots \beta_k)$ the vector of parameters.

The calculation of the maximum likelihood is simplified using the log of equation (4.1) above. Thus the accepted log likelihood is

$$L(\beta) = \ln[l(\beta)] = \sum_{i=1}^{n} \{y_i \ln[\pi(x_i)] + (1-y_i)\ln[1-\pi(x_i)]\} \tag{4.2}$$

To find the values of β that maximise the log likelihood function (4.2), equation (4.2) can be differentiated with respect to β and setting the resulting equations to zero. These equations are as follows.

$$\sum_{i=1}^{n} x_i[y_i - \pi(x_i)] = 0 \qquad (4.3)$$

$$\sum_{i=1}^{n} [y_i - \pi(x_i)] = 0 \qquad (4.4)$$

Equations (4.3) and (4.4) are called the maximum likelihood equations. Because these equations are non-linear in β, numerical algorithms can be used to solve the nonlinear equations. In SAS (1990), the Fisher-scoring algorithm is used.

3.2.3 Variable Selection

The generalised linear models approach offers modellers the ability to model a variety of data types including discrete, categorical, ordinal and continuous under a single theoretical and computational framework (Yee & Mitchell 1991). For the most part, this study has followed the strategy proposed by Hosmer & Lemeshow (2000 p.91). This strategy however, is not one of definitive rules, but rather a sound guide to follow.

In this study this strategy began by ensuring that the 2 x 2 contingency table between each dummy variable and the response variable had no zero filled cells. In logistic regression, zero filled cells cause computational errors with fit statistics. When zero cells were encountered, the categories were either grouped with a similar dummy variable or deleted when it involved only a few records and no similar group could be found.

At this stage, Hosmer and Lemeshow (2000) suggested a univariate analysis of all covariates to select those with at least a moderate (p-value $< .25$ for the individual Wald chi-square test) association with the response variable. The univariate model also provides a parameter estimate that has not been adjusted by another through interaction or confounding. These parameter estimates are used later in the analysis to detect confounding and interactions.

The next step involved stepwise logistic regression using SAS (1990). The stepwise procedure was used to identify those covariates which seemed to be statistically important. A p-value < .05 was used for both entry and removal. The stepwise selection procedure, based on the likelihood ratio, identifies at any step, the variable which produces the greatest change in the likelihood relative to a model not containing that variable. After the inclusion of a variable, all variables that no longer met the Wald chi-square probability of .05, were removed. The statistical inclusion of a variable using stepwise regression is an important step in model fitting, however as emphasised by Hosmer and Lemeshow(2000), variables must also be selected because of their biological significance. Those covariates not chosen by the stepwise procedure but were thought to have biological importance were continually returned to the analysis to ensure their parameter estimates were not statistically significant from zero. In no cases could the inclusion of a statistically insignificant variable be justified.

The next step involved fitting the full multivariate model and examining the Wald test statistic for each individual covariate. Large Wald statistics indicate a high contribution to the model by the covariate. Although the score test and the Wald chi-square test give an indication of the variables contribution to the model and thus its possible effect on the likelihood ratio, the actual effect on the likelihood was tested by removing the covariate from the model and then refitting the model. This process of deleting and refitting was carried out until a ranking of the covariates was made, based on their effect on the likelihood ratio and their Wald test statistic. This was the basis for determining the order that covariates should be removed from the model.

Because the stepwise procedure usually yielded far more covariates (up to 45) than would be considered parsimonious, it was necessary to remove covariates that significantly increased the likelihood ratio. In this study it was accepted that, in an attempt to find a parsimonious model, there would be a decrease in the likelihood ratio between the full multivariate model and the reduced model. While searching for a parsimonious model, it was essential that, no known biologically important covariates were removed and those covariates which contributed least to the increase in the likelihood ratio were removed first. The final step was the grouping of dummy variables with similar slope by testing, at a .05 level of significance, whether similar coefficients were significantly different.

Once a preliminary model was fit, the scale or the curve form of the continuous variables was evaluated. Because in the beginning of the modelling process, the scale of the continuous variables were unknown or only thought to be known, the procedure proposed by Hosmer & Lemeshow (2000, p.99) to determine the scale, was followed. Once an idea of the correct scale was established, the appropriate transformations were tested. The method of trying every possible transformation using the stepwise procedure was attempted and quickly discarded.

The next stage involved checking for interactions. Using the coefficients from the univariate models, variables where the sign of their coefficients had changed or their coefficient changed markedly when compared to the univariate model, were identified. These cases indicated the presence of either confounding or an interaction. Using the stepwise regression procedure, while forcing all original covariates into the model, the interaction terms were tested. As with normal stepwise regression, the interactions must have a p-value $< .05$ for the Wald statistic. If the change in the likelihood ratio is not significant, the interaction term is considered a confounder and the interaction term not included in the model. If the likelihood ratio increase is significant, then the interaction terms is truly an interaction and should be included in the model. This process of testing possible interactions was carried out for all variables which had marked changes in their coefficients. Only interactions, which were biologically possible, were kept in the final model.

To ensure that the final model was in fact biologically sound or followed known expectations, two dimensional and surface plots of the models were made. Each parameter was evaluated individually to see if its contribution was in fact sound. Variables, which clearly behaved against the expected relationship, were once again evaluated using the univariate model. If behaviour was clearly unexpected, variables were removed and the model refit.

3.2.4 Goodness of Fit

3.2.4.1 Computational Statistics

A goodness of fit assessment was done after all the important variables and interactions were entered into the model. Goodness of fit is a description of how effective the model is in describing the response variable. Unlike linear regression, the methods for assessing goodness-of-fit for logistic regression are still begin developed. In the literature, there is a great deal of criticism concerning modellers lack of concern or lack of understanding in performing goodness-of-fit tests. One example is assessing the goodness-of-fit through the likelihood ratio test. As Hosmer et al. (1988) pointed out, this is no different than saying a model fits using the F-test in linear regression. Another example is in the presentation by Ertsen et al. (1998) where several models were evaluated using the ($\hat{C}$) statistic. The authors suggested that a model with a p-value, based on the $\hat{C}$ statistic, of less than 0.05 was poorly predicted. If the p-value was between 0.05 and 0.5, the model predicted moderately well and a model with a p-value of greater than 0.5 predicted very well. This ranking of performance based on the $\hat{C}$ statistic is incorrect, since one cannot select the „best model", using the $\hat{C}$ statistic, from a collection of models that all fit (Hosmer & Lemeshow 2000, p.183).

Another problem deals with the Pearson Chi-square and Deviance statistic. During the model building stage, the degrees of freedom for tests are based on the number of variables in the competing models. However, in assessing the goodness of fit, concern is focused on the number of covariate patterns. A covariate pattern is a unique combination of values for the covariates in the model. When the number of observations increase and the number of covariate patterns increase, the distributional results are said to be based on *n-asymptotics*. When the number of observations increases but not the number of covariate patterns, the distributional results are said to be based on *m-asymptotics*. When Chi-square statistics are calculated under *n-asymptotics,* the p-values are incorrect. The problem with the p-values comes from the fact that under *n-asymptotics*, the required minimum of 5 observations per cell is not met.

For this reason, the Chi-square statistic and the Deviance statistic were not used to evaluate the models for goodness-of-fit. The alternative test was the Hosmer and Lemeshow test statistic ($\hat{C}$) (Hosmer et al. 1988) using two different grouping strategies. In the first grouping strategy, the ($\hat{C}$) statistic was calculated by arranging the predicted responses in ascending order, then grouping them into 10 classes (*k* groups), each with approximately the same number of predictions. The second grouping strategy was to use defined cutpoints, which in this study were 10 fixed probability classes. For each model the Hosmer Lemeshow goodness-of-fit criterion ($\hat{C}$), using both grouping strategies, was calculated according to the Pearson Chi-square statistic:

$$\hat{C} = \sum_{k=1}^{g} \frac{(o_k - n_k \bar{\pi}_k)^2}{n_k \bar{\pi}_k (1 - \bar{\pi}_k)}$$

Where n_k is the number of observations in the k^{th} group, o_k the number of observed responses in the k^{th} group and $\bar{\pi}_k$ is the average estimated probability for the k^{th} group.

The reason for using both grouping strategies was to deal with problems that arise from goodness-of-fit testing when the estimated probabilities, the proportion of the response variable that is 1 in relation to the total number of observations, are small (< 0.1) or very large (> 0.9), something that was common in the models used in this study. Hosmer et al. (1988) cautioned the use of any fit statistic in these cases. The problem is similar to the problem with the Chi-square statistic and the Deviance statistic where the required minimum of 5 observations per cell are not met. In an example with a model with a very small estimated probability, the authors used both grouping strategies using the rational that, although the p-values were inaccurate, if both grouping strategies proved to have an insignificant fit, the p-values were accurate enough for hypothesis testing. This study required the $\hat{C}$ statistic for both grouping strategies to be insignificant.

The $\hat{C}$ statistic is a very sensitive statistic when the model does not fit. This means its value can vary drastically, from having a p-value of 0.4 (model fits) to have a p-value of .002 (model does not fit), with the addition or removal of a single independent variable. When the $\hat{C}$ statistic behaves irradically, it is a good indication that there are still problems with the model fit: most likely an independent variable has the wrong scale, an important variable is missing or an interaction term is missing. This study found that when the model truly fits, $\hat{C}$ becomes stable, such that small changes (addition or removal) of the least important independent variables, results only in small changes in $\hat{C}$ statistics.

3.2.4.2 Regression Diagnostics

In linear regression, residual plots are essential to test assumptions and evaluate goodness-of-fit. In logistic regression, although the residual plots do not possess the same importance as in linear regression, they however can be useful in an analysis by identifying outliers and poorly fit data. There are three important diagnostic plots; Delta Chi-Square versus $\hat{\pi}_j$, Delta Deviance versus $\hat{\pi}_j$ and Delta Betas versus $\hat{\pi}_j$. Each point in these plots reflects the size of the change in the chi-square, deviance and the estimated parameters, when that particular covariate pattern is removed from the dataset and the model is refit. In Hosmer & Lemeshow (2000) there is an excellent discussion about the uses and interpretation of these plots. These plots were used for two purposes. The first was in helping determine if the model was nearing a good fit. If the model nears a good fit, there are usually some values in the diagnostic plots that are "very" extreme. This, in conjunction with, an unstable $\hat{C}$ statistic suggests that the model still needed more work. The second use was in isolating events that are illogical and go against the logic of the model. These appear as large residuals in the plots and can easily be isolated and reviewed. A good example is a subplot with 100% blueberry at time 1 then after 5 years having no blueberry at all, when there have been no notable changes in the stand. Understanding the nature of blueberry, one could not logically explain this, unless there was some typographical error or some intervention by man such as liming. These illogical events were noted, however, data was never deleted unless it was clearly a typographical error. These notes would be used when the model was applied to help identify situations where the model could behave poorly.

3.2.4.3 Refinement

A model is said to be refined when the range of predictions produced by the model, span the full probability range between 0 and 1 (Pearce & Ferrier 2000a). Moderate refinement is essential when assessing a models performance. A model that is poorly refined but is well calibrated is very unlikely to discriminate well, even though it is possible for a model that is well calibrated and well refined to discriminate poorly, it is less likely. Thus as the variance of the predicted probabilities increases, the refinement increases. Refinement was evaluated graphically.

3.2.4.4 Classification Tables and the Ability to Discriminate

A 2 x 2 classification table between the observed values, in this case the dichotomous (0, 1) and the predicted values dichotomised using a chosen cutvalue, can be constructed. The terminology used to address the parts of the 2 x 2 classification table are important for the following discussion and are therefore are summarised in Table 3-1. If an event occurred (1) and the model predicted that an event occurred (1), this observation would be represented in the true positive cell. The proportion of correctly predicted events over the total number of observed events is referred to as the sensitivity (true positive/(true positive + false negative)). If an event occurred and the model predicted that it did not occur, this observation would be represented in the false negative cell. If an event did not occur (0), non-event, and the model predicted that an event did not occur (0), this observation would be represented in the true negative cell. The proportion of correctly predicted non-events over the total number of observed non-events is referred to as the specificity (true negative/(true negative + false positive)). If an event did not occur and the model predicted that it did occur, this observation would be represented in the false positive cell

Table 3-1: Naming of the cells within a 2 x 2 contingency table.
Tabelle 3-1: Bezeichnung der Felder einer 2 x 2 Kontingenztafel für die beobachtet Klassifizierung und jene nach den Modellen.

	Observed	
Predicted	1	0
1	True Positive (Sensitivity)	False Positive
0	False Negative	True Negative (Specificity)

If a model is well calibrated and has moderate refinement, the models ability to discriminate can be evaluated using a classification table (Pearce & Ferrier 2000a). However, discrimination cannot be used as a measure to assess goodness-of-fit since it does not meet the criteria for goodness-of-fit: "that the distances between observed and expected values be unsystematic and within the variation of the model" (Hosmer & Lemeshow 2000, p157). It is therefore possible to find a model that discriminates well and fits poorly. Furthermore, the ability to discriminate is based on the definition of the cutoff value. There are several intuitive cutoff/threshold values that one could use: 1) 0.5 which represents an even split; 2) where the maximum discrimination occurs (sensitivity + specificity are at a maximum); 3) where maximum discrimination for both sensitivity and specificity, occur together; 4) at the a priori probability level; 5) at a probability level where the a priori probability is found in the predicted data. The choice of the cutoff value for habitat modelling is usually based on the a priori probability of the occurrence of the species of interest (Pearce & Ferrier 2000a). However, any probability level can be chosen, if justifiable.

One measure of discrimination that it is independent of both species prevalence and decision threshold is the area under the receiver operating characteristic curve (ROC) (Hanley & McNeil 1982; Hanley & McNeil 1983; Pearce & Ferrier 2000a; Pearce & Ferrier 2000b). It plots the probability of predicting an event correctly (sensitivity) versus the probability of predicting a non-event as an event (1-specificity) for an entire range of cutpoints Figure 3-3. Essentially, it is a summary of all the sensitivities and 1-specificities, found in all the 2 x 2 contingency tables for all the unique cutpoints within the data. There are two uses for this plot; first, it can aid a modeller in choosing an appropriate cutoff value and second, it can aid a modeller in choosing one model over another when both models fit.

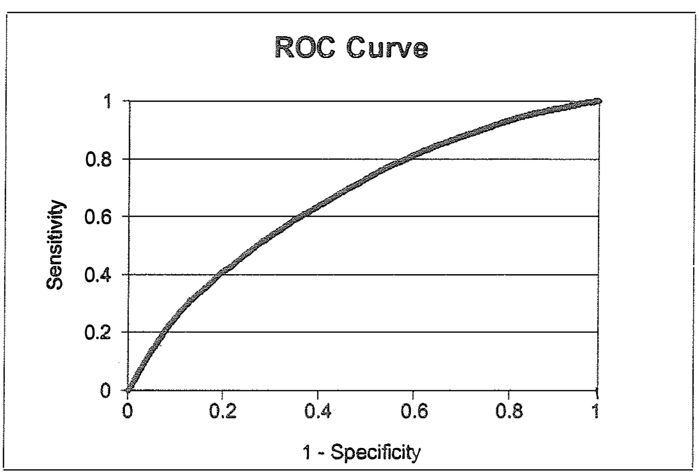


Figure 3-3: Receiver Operating Characteristic curve.
Abbildung 3-3: Die „Receiver Operating Characteristic" Kurve.

This is done by comparing their ability to discriminate using the areas under the curve. Areas of 0.5 to 0.7 indicate poor discrimination, 0.7 to 0.8 indicate moderate discrimination and rates higher than 0.9 are excellent (Hosmer and Lemeshow, 2000 p.162).

3.3 Logarithmic Regression

3.3.1 Model Specification and Variable Selection

Under a two model system, the logistic model determined whether a particular response variable was present or absent in the future. If it was decided that it would be present in the future then the next question is, in what quantity? To quantify the response variables, a natural log transformation of the response variable was chosen taking the form;

$$\ln(y) = \beta_o + \beta_1 x_1 + \beta_2 x_2 ... + \beta_k x_k$$

The choice to use a log transformation was based the fact that the distribution of the dependent variables were skewed to the right and log transformations aided in reducing skewness. This was supported after testing several model forms with the log transformations yielded significantly better fits than untransformed models in terms of R^2. The one drawback of using a log transformation is the transformation bias when untransforming the response variable. One option to correct this bias, is to add one-half of the model mean square error (MSE) to the logit of the final equation (Meyer 1941; Miller 1984).

$$\ln(y) = \beta_o + \beta_1 x_1 + \beta_2 x_2 ... + \beta_k x_k + MSE/2$$

To find the best fitting model, least squares methods were used. As with the logistic models, stepwise regression was used to identify the independent variables that were most related to the response variable. In search of a parsimonious model, in some cases, variables, which had estimated parameters that were significantly different from zero, were removed. The continuous variables were tested for scale and possible interactions. The final step was the grouping of dummy variables with similar slopes. Plots of the final models were made to ensure that model behaviour under different conditions was consistent with known behaviour.

3.3.2 Residual Analysis

The scatter of the residuals plotted against the predicted values and each of the independent variables, where examined to ensure that the plotted residuals did not display an apparent pattern and where scattered uniformly and regularly around the null axis. A trend in the residual plots against the predicted values would have suggested that the model was inadequate and one or more of the independent variables required some type of transformation. To test the assumption of homoscedasticity, a plot of the residuals against each independent variable was carried out. If the width of the residuals varied systematically, for different values of an independent variable, the variance of the residuals was not constant for different values of the independent variable, a violation of the assumption of homoscedasticity. It should be noted that the assessment of the residuals was complicated by the fact that the response variables were ordinally scaled integers, from 1 – 10, thus the scatter plots possessed the „integer effect". To aid in this assessment, the means of the residuals, grouped into 10 classes were also plotted and evaluated. The variance inflation factor was used to test for multicollinearity. Variables with high variance inflation factors were systematically removed from the model until no variable had a variance inflation factor greater than 5 (Van Laar 1991).

3.4 The Development of the Input Dataset for the Logarithmic Models

The choices of how to model the quantification of the growth and browse classes was not simple. The first question was, on what basis was the stratified dataset, to be used as input to the logarithmic model, to be made? Two choices were available, 1) use only the observations that were *„correctly predicted"* by the logistic model or, 2) use only the observations where the percent share of the regen class or browse class at time 2 was greater than 0. This dataset is referred to as the *„observed only"* dataset.

To answer this question, the performance of the combined logistic and regression model system was evaluated, using both input datasets, for the BLUEBERRY BROWSE classes. The methodology was simple, the logistic model for blueberry, when blueberry was present at time 1, was already fit and considered a constant (Table B - 15). To construct the *„observed only"* dataset, all observations where the observed percent share of blueberry at time 2 was zero, were deleted. To construct the *„correctly predicted"* dataset, the cutoff probability was set to the a priori probability for blueberry, which was 0.84, and all observations that were incorrectly classified were deleted. The choice to use the a priori probability was made based on the fact that it was grounded to the distribution of the original data. The cutoff probability could theoretically have been set at any probability level resulting in significantly different results.

Using each of the datasets, two linear regression models with the natural log of the percent share of blueberry at time 2 as the dependent variable were fit. In order to use a natural logarithm, the dependent variable was re-scaled from 0 – 10 to 1 – 11, however all results are presented and discussed on the original 0 – 10 scale. The *„observed only"* model with its fit statistics are presented in (Table 3-2). The *„correctly predicted"* model with its fit statistics is presented in (Table C - 15). To evaluate the overall performance of the combined models, the probability of blueberry, for each observation, was predicted for the original blueberry dataset (the dataset used to fit the logistic model). Then, it was again necessary to specify a cutoff probability to determine if blueberry would be present at time 2. If the logistic model, based on the cutoff probability, predicted that there would be blueberry present at time 2, the percent share of blueberry at time 2 was predicted using the two linear regression models. A range of cutoff probabilities was tested to see how the model performance changed with respect to varied cutoff probabilities.

Histograms presenting the observed and predicted frequencies, were plotted for each percent share class, for different cutoff probabilities. The results for the *„correctly predicted"* versus the *„observed only"* dataset are shown in Figure 3-4 and Figure 3-5 respectively.

Once the results were obtained, it was necessary to specify the criteria that would constitute "good" model performance. The first criteria was an evaluation of the fit between the *„correctly predicted"* and the *„observed only"* models. From Table C - 15 and Table 3-2 it is seen that the *„correctly predicted"* model has a higher coefficient of determination (R^2=0.7489) compared to the *„observed only"* (R^2=0.5455) . The reason for this significant difference has to do with the input dataset. The *„observed only"* is an improvement over the whole dataset because of the stratification. But the stratification is one sided, such that the variation of the data that is used, still possess the full variability for those observations. In the *„correctly predicted"* dataset, the observations that had the greatest variability were removed because they would have been poorly predicted by the logistic model. The concept is that there is no need to continue to model the poorly predicted observations, the logistic model has already made choice of whether or not blueberry will be there or not at time 2. All wrongly classified observations are already in error. There is no need to continue to proliferate the error by including those in the second quantitative model.

Table 3-2: Logarithmic regression for BLUEBERRY – 1 using the „*observed only*" dataset. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle 3-2: Logarithmische Regression für Heidelbeere – 1, geschätzt aus den „Observed only" Daten. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, ihre Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle steht das Bestimmtheitsmaß und die Anzahl der Beobachtungen.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	0.47626	0.05744	<.0001
A_HESH_T1	Blueberry Browse	0.14781	0.00271	<.0001
ELEV	Elevation	0.01313	0.00139	<.0001
SLPE	Slope	-0.01338	0.00242	<.0001
STANGSH_T2	Pole Stand	-0.01098	0.00197	<.0001
INTVAL	Interval Value	0.03930	0.00979	<.0001
GVD5	Luxuriant Moss Type	0.08772	0.01579	<.0001
GVD18	Seep Vegetation Type	-0.27217	0.07029	0.0001
GVD4,12	Moderhumus in Conifer Stands or Competing Grass Cover	-0.08984	0.01515	<.0001
STD0_T1, STD1_T2	No Trees in Angle Count or Norway Spruce	-0.05416	0.01020	<.0001
STD10_T2	Beech	-0.15752	0.05485	0.0041
SCD5	Soil Group 5	0.05065	0.01722	0.0033
SCD7	Soil Group 7	0.13601	0.05211	0.0091
GZD1	Growth Zone 1	-0.05857	0.01675	0.0005

$R^2 = 0.5455$
n = 4670

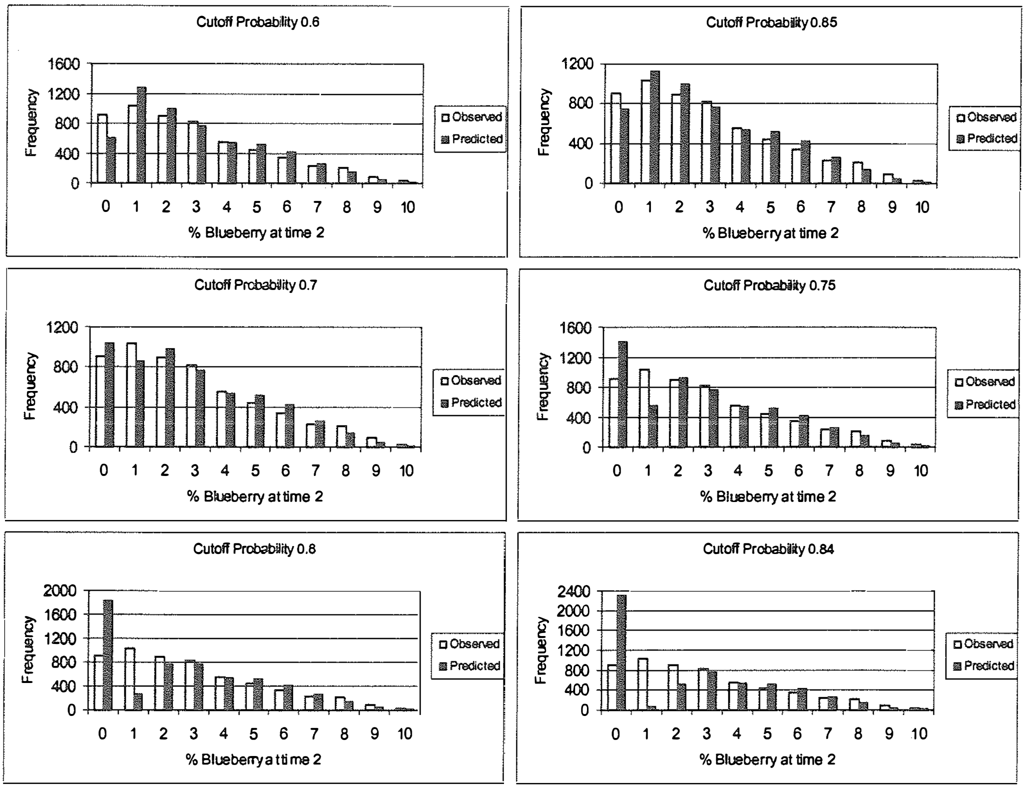


Figure 3-4: Distribution of observed versus the predicted values for different cutoff probabilities based on the dataset fitted using the *„correctly predicted"* data. The A Priori Probability for blueberry is 0.84.

Abbildung 3-4: Verteilung von beobachteten und geschätzten Werten für verschiedene Schwellenwerte für den Datensatz mit richtig vorhergesagten Werten („Correctly Predicted"). Die *a priori* Wahrscheinlichkeit für Heidelbeere beträgt 0.84.

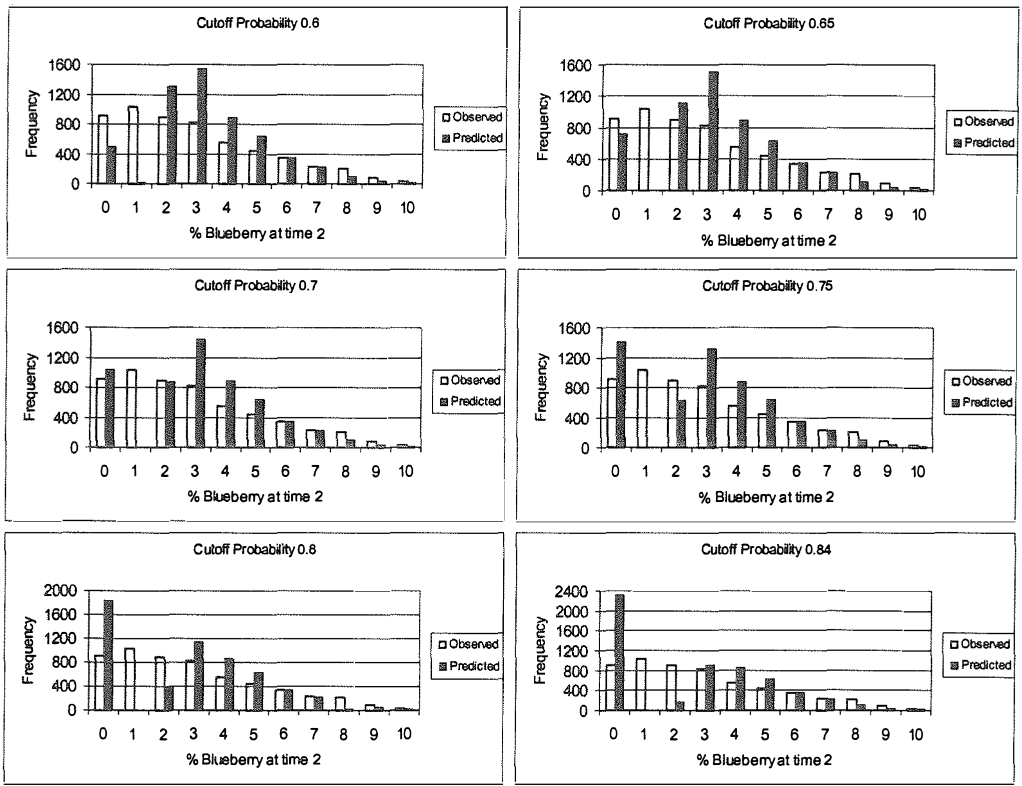


Figure 3-5: Distribution of observed versus the predicted values for different cutoff probabilities based on the dataset fitted using the *„observed only"* data. The A Priori Probability for blueberry is 0.84.

Abbildung 3-5: Verteilung von beobachteten und geschätzten Werten für verschiedene Schwellenwerte für den ursprünglichen Datensatz „Observed Only". Die *a priori* Wahrscheinlichkeit für Heidelbeere beträgt 0.84.

When viewing the histograms, it was clear that the predictions using the *„observed only"* dataset significantly underestimated the percent share 1 class, in all cases. This underlined the fact that the predictions should have a similar distribution to the observed data and are therefore, unbiased. Analysing the results of the *„correctly predicted"* dataset, it is clear that somewhere between a cutoff value of 0.65 and 0.70 the distribution of the predicted is very near the observed. It is not a coincidence that at a cutoff value of 0.68, the ratio of the predictions where there is blueberry at time 2 over all observations, is 0.84, the a priori probability. This result is not only convenient but provides a sound basis for choosing cutoff probabilities. One may argue that other factors could be considered, such as maximising discrimination or maximising sensitivity and specificity. From the logistic run, maximum discrimination was achieved at a cutoff probability of 0.55. Maximisation of both sensitivity and specificity was at a cutoff probability of 0.80. Clearly from the results presented in Figure 3-4 and Figure 3-5, neither of these choices would be acceptable in terms of the distribution of the predictions.

Because the predictions of the percent share at time 2 were continuous and needed to be categorised, the cutoff points for the different classes also affected the results. Several different cutoff strategies were tested in order to improve the distribution of the predictions of the *„observed only"* dataset. It was possible to improve the performance in the percent share 1 class by raising its maximum cutoff point, however this was always at the cost of another class. So, why did the *„observed only"* dataset predictions behave so poorly? The most obvious reason is the intercept of 0.47626 (natural logarithmic scale using 1 – 11 to represent 0 - 10). This intercept was expected since all observation with no blueberry at time 2 were deleted, hence there were no zeros in the dataset. Thus, there were no null observations in the data to force the model through zero.

Comparatively, the *„correctly predicted"* dataset included zeros in the dataset thus the intercept was --0.09560 (natural logarithmic scale using 1 – 11 to represent 0 - 10), much nearer to zero. The final choice for cutoff points for categorising the predictions from the *„correctly predicted"* dataset are presented in Table 3-3.

Table 3-3: The cutoff points for categorising the predictions for the „*correctly predicted*" dataset.
Tabelle 3-3: Die Schwellenwerte zur Klassifizierung mit den Modellen für den „Correctly Predicted-Datensatz".

Percent Blueberry Class	Predicted Range
0	0
1	>0 to 1
2	>1 to 2
3	>2 to 3
4	>3 to 4
5	>4 to 5
6	>5 to 6
7	>6 to 7
8	>7 to 8
9	>8 to 9
10	>9

Because the above analysis was based only on half of the blueberry data, the same procedure for blueberry, when blueberry was not present at time 1, was carried out. The results were similar supporting the „*correctly predicted*" dataset as the input dataset for the logarithmic models.

Based on the results above, the modelling strategy, where the correctly classified observations, based on the a priori probability, are used as the input dataset for the logarithmic model was chosen. This methodology was followed for the development of the remainder of the logarithmic models.

3.5 Evaluation of Overall Performance

The evaluation of model performance should be done using a validation procedure on an independent dataset (Pearce & Ferrier 2000a). When it is done on the same dataset the model will tend to always perform in an optimistic manner. One option at the beginning of the modelling process was to exclude a portion for validation. However it was decided not to do this for two reasons. The first was that for some of the response variables, the datasets would be reduced to a size that could sacrifice model fit. Secondly, a dataset from 1991 in the Gleinalm region of Austria was already available and there were plans to collect the time 2 data in 2001. This would be an excellent dataset to evaluate the model fits.

Because a two model system was applied, there was a temptation to evaluate the performance of each model, from a model pair independently. For the logistic regression, one measure of performance is through the ability to discriminate, which was tested using the area under the ROC curve. However, for the regression it was not as simple. The regression was based on a reduced dataset, which would be expected to be biased. This was confirmed using the simultaneous F-test. The simultaneous F-test involves regressing the observed values against the predicted values of the *entire* dataset. The resulting simple linear equation would be in the form of

$$y = a + b(x).$$

Using an Analysis of Variance (ANOVA) table it is possible to test if the predicted values are not significantly different from the observed, thus testing the hypothesis H_0: a=0 and b=1 an intercept of 0 (a=0) and a slope of 1 (b=1). Any significant differences would be considered a bias. Both the *„correctly predicted"* and the *„observed only"* datasets, discussed in section (3.4), were biased.

This leads to the recognition that overall model performance could not be evaluated on the sum of its parts, but rather only as a whole. This is intuitively correct, since the regression model is not independent of the logistic model. Firstly, because the choice of whether a particular response variable will be present or not in the future, is a decision made by the logistic model, and secondly, because the model that predicts the quantity is modelled using only those observations that were correctly predicted by the logistic model.

Therefore, in addition to the individual model performance measures, evaluation of the overall performance each of the two model pairs (logistic and logarithmic regression) was done using the Efficiency (EF) measure according to Mayer & Butler (1993). Efficiency is calculated as

$$EF = 1 - \frac{\sum (Y_{observed} - Y_{predicted})^2}{\sum (Y_{observed} - \overline{Y}_{observed})^2}.$$

The efficiency is similar to the coefficient of multiple determination (R^2), however because the value of EF can be between $-\infty$ and 1, its interpretation is different. An EF value of 0 suggests that the model is no better than the average, an EF value nearing 1 suggests an efficient model, a negative EF value suggests that the model is biased.

As seen in section (3.4) the evaluation of performance must also be based on a comparison of the future distribution of predicted values compared to the observed distribution. Reimoser and Zandl (1994, pp.94) stated that judgements of indices should not be based on single plots but rather on larger areas, at least 100ha. Because this is important, the distribution of predicted values must be similar to the distribution of the observed. It is therefore necessary to evaluate the performance of each of the models in obtaining the correct distribution. To accomplish this, the predicted frequency of each quantity class, for different cutpoints, was plotted against the frequency histogram for observed quantities.

In summary, the performance of the models will be assessed; 1) individually, and 2) as model pairs using the efficiency statistic and by evaluating the predicted distributions to the observed.

4 RESULTS

4.1 Logistic Models

In order to predict the 14 HSI parameters, 28 logistic models were fit using stepwise regression. The models can be divided into two categories, those predicting the probability of the presence or absence of the future growth classes and those predicting the probability of the presence or absence of the wildlife browse classes. Appendix B presents the tables containing the important parameters that both statistically contribute in the prediction of the response variable, their associated estimated coefficient, their standard error and their respective Wald Chi-Square probability. Below each table is the number of observations in the dataset, the a priori probability, the probability level where the a priori probability was found in the predictions (threshold), the Hosmer and Lemeshow test results (calculated using an equal number of observations per group) and the area under the ROC curve. Example Tables are presented in the text for CONIFER BROWSE. Note, these example tables do not appear as the first example but rather maintain the original ordering. CONIFER BROWSE was selected as an example because it represented both the forest and wildlife disciplines. A summary of the fit statistics are presented in Table 4-5.

4.1.1 Growth Classes

REGEN I

For REGEN I a total of two models were fit. The first model represented the case where REGEN I was present at time 1 with trees in the overstory (REGEN I – 1 with trees). The parameters and the corresponding fit statistics are represented in Table B - 1. The second model represented the case where REGEN I was present at time 1 and there were no trees in the overstory (REGEN I - 1 with no trees). The parameters and the corresponding fit statistics are represented in Table B - 2. For both models all the variables are significant based on the Wald chi-square test at level $\alpha=0.05$. For the REGEN I – 1 with trees model, the value for the Hosmer Lemeshow statistics is 11.4682 (p-values of 0.1766 with 8 degrees of freedom). For the REGEN I – 1 no tree model the value for the Hosmer Lemeshow statistic is 10.0366 (p-values of 0.2625 with 8 degrees of freedom). These p-values are large, far exceeding the $\alpha=0.05$ level so there is no strong evidence showing a disagreement between the predicted and observed presence and absence of REGEN I at time 2. The models are statistically well-fitted. The areas under the ROC curves are .76 and .77 respectively, suggesting that they discriminate moderately well.

For the REGEN I – 0 with trees case, no model was fit because the relative frequency of REGEN I encroaching onto a site at time 2, when it is not present at time 1 and is overtopped by an overstory is 0.9%. In application, it is suggested that in these cases, 0.9% of the subplots be randomly chosen to have Regen I at time 2.

REGEN II

For REGEN II a total of 4 models were fit. The first model represented the case where REGEN II was present at time 1 with trees in the overstory (REGEN II – 1 with trees). The parameters and the corresponding fit statistics are represented in Table B - 3. The second model represented the case where REGEN II was present at time 1 and there were no trees in the overstory (REGEN II - 1 with no trees). The parameters and the corresponding fit statistics are represented in Table B - 4. The third model represented the case where REGEN II was not present at time 1 with trees in the overstory (REGEN II – 0 with trees). The parameters and the corresponding fit statistics are represented in Table B - 5. The fourth model represented the case where REGEN II was not present at time 1 and there were no trees in the overstory (REGEN II - 0 with no trees). The parameters and the corresponding fit statistics are represented in Table B - 6. In all the models, all the variables are significant based on the Wald chi-square test at level α=0.05. For the REGEN II – 1 with trees model, the value for the Hosmer Lemeshow statistics is 8.2781 (p-values of 0.4068 with 8 degrees of freedom). For the REGEN II – 1 no tree model, the value for the Hosmer Lemeshow statistic is 7.8098 (p-values of 0.4523 with 8 degrees of freedom). For the REGEN II – 0 with trees model, the value for the Hosmer Lemeshow statistic is 3.0400 (p-values of 0.9318 with 8 degrees of freedom). For the REGEN II – 0 no tree model, the value for the Hosmer Lemeshow statistic is 12.5077 (p-value of 0.1299 with 8 degrees of freedom). These p-values are large, far exceeding the α=0.05 level so there is no strong evidence showing a disagreement between the predicted and observed presence and absence of REGEN II at time 2. The models are statistically well-fitted. The areas under the ROC curves are .76, .72, .79 and .85 respectively, suggesting that the models discriminate moderately well.

4.1.2 Wildlife Browse Classes

For the wildlife browse classes each dataset was divided into two datasets based on whether the wildlife browse class was present or absent at time 1. Therefore for each wildlife browse class, two models were fit totalling 20 models.

NO BROWSE

For the NO BROWSE class a total of two models were fit. The first model represented the case where NO BROWSE was present at time 1 (NO BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table B - 7. The second model represented the case where NO BROWSE was not present at time 1 (NO BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table B - 8. For both models all the variables are significant based on the Wald chi-square test at level α=0.05. For the NO BROWSE – 1 the value for the Hosmer Lemeshow statistics is 5.6990 (p-values of 0.6809 with 8 degrees of freedom). For the NO BROWSE – 0 model the value for the Hosmer Lemeshow statistic is 12.9188 (p-values of 0.1147 with 8 degrees of freedom). These p-values are large, far exceeding the α=0.05 level so there is no strong evidence showing a disagreement between the predicted and observed values. The models are statistically well-fitted. The areas under the ROC curves are .83 and .73 respectively, suggesting that they discriminate moderately well.

CONIFER BROWSE

For the CONIFER BROWSE class a total of two models were fit. The first model represented the case where CONIFER BROWSE was present at time 1 (CONIFER BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table 4-1. The second model represented the case where CONIFER BROWSE was not present at time 1 (CONIFER BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table 4-2. For both models all the variables are significant based on the Wald chi-square test at level α=0.05. For the CONIFER BROWSE – 1 the value for the Hosmer Lemeshow statistics is 6.2266 (p-values of 0.6219 with 8 degrees of freedom). For the CONIFER BROWSE – 0 model the value for the Hosmer Lemeshow statistic is 12.0080 (p-values of 0.1508 with 8 degrees of freedom). These p-values are large, far exceeding the α=0.05 level so there is no strong evidence showing a disagreement between the predicted and observed values. The models are statistically well-fitted. The areas under the ROC curves are .74 and .73 respectively, suggesting that they discriminate moderately well.

Table 4-1: Logistic regression for Conifer Browse – 1. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle 4-1: Logistische Regression für Nadelbäume – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	8.4313	0.3625	<.0001
INTVAL	Interval Value	-1.1694	0.0618	<.0001
STD1_T2	Norway Spruce	-0.3365	0.0632	<.0001
SCD4,17,18	Soil Group 4, 17, 18	0.3120	0.0609	<.0001
SCD6	Soil Group 6	0.6273	0.2340	0.0073
GVD1	Shade Herb Type	-0.5952	0.1169	<.0001
C_BA	Change in Basal Area	-0.0117	0.00353	0.0009
A_NOSH_T1	No Browse	-0.1828	0.0135	<.0001
GZD12,17,18	Growth Zone 12, 17, 18	0.3413	0.0825	<.0001
SSD1_T2	1 Layer Stand	-0.1576	0.0680	0.0204
JUNGIISH_T1	Regen II	-0.0214	0.00785	0.0063
STANGSH_T2	Pole Stand	-0.1327	0.0111	<.0001

Hosmer-Lemeshow statistic = 6.2266 with 8 DF (p=0.6219)
ROC = .74
A Priori Probability = .69, Threshold Probability = .63
n = 6301

Table 4-2: Logistic regression for Conifer Browse – 0. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle 4-2: Logistische Regression für Nadelbäume – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	-4.2024	0.3968	<.0001
ELEV	Elevation	0.2668	0.0351	<.0001
ELEV²	Elevation Squared	-0.0122	0.00181	<.0001
INTVAL	Interval Value	0.3206	0.0624	<.0001
STD0_T2	No Trees in Angle Count	1.3140	0.0837	<.0001
GZD18,20	Growth Zone 18, 20	0.7159	0.0910	<.0001
SSD1_T2	1 Layer Stand	-0.7500	0.1228	<.0001
SSD2_T2	2 Layer Stand	-0.5188	0.1373	0.0002
GVD1	Shade Herb Type	-0.6053	0.1093	<.0001
GVD6	Sparse Moss Type	0.3849	0.0745	<.0001

Hosmer-Lemeshow statistic =12.0080 with 8 DF (p= 0.1508)
ROC = .73
A Priori Probability = .11, Threshold Probability = .20
n = 11758

Deciduous Browse

For the Deciduous Browse class a total of two models were fit. The first model represented the case where Deciduous Browse was present at time 1 (Deciduous Browse – 1). The parameters and the corresponding fit statistics are represented in Table B - 9. The second model represented the case where Deciduous Browse was not present at time 1 (Deciduous Browse - 0). The parameters and the corresponding fit statistics are represented in Table B - 10. For both models all the variables are significant based on the Wald chi-square test at level $\alpha=0.05$. For the Deciduous Browse – 1 the value for the Hosmer Lemeshow statistics is 6.4478 (p-values of 0.5972 with 8 degrees of freedom). For the Deciduous Browse – 0 model the value for the Hosmer Lemeshow statistic is 3.3892 (p-values of 0.9076 with 8 degrees of freedom). These p-values are large, far exceeding the $\alpha=0.05$ level so there is no strong evidence showing a disagreement between the predicted and observed values. The models are statistically well-fitted. The areas under the ROC curves are .70 and .78 respectively, suggesting that they discriminate moderately well.

SHRUB BROWSE

For the SHRUB BROWSE class a total of two models were fit. The first model represented the case where SHRUB BROWSE was present at time 1 (SHRUB BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table B - 11. The second model represented the case where SHRUB BROWSE was not present at time 1 (SHRUB BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table B - 12. For both models all the variables are significant based on the Wald chi-square test at level α=0.05. For the SHRUB BROWSE – 1 the value for the Hosmer Lemeshow statistics is 5.9022 (p-values of 0.6582 with 8 degrees of freedom). For the SHRUB BROWSE – 0 model the value for the Hosmer Lemeshow statistic is 14.2304 (p-values of 0.0760 with 8 degrees of freedom). These p-values exceed the α=0.05 level so there is no evidence showing a disagreement between the predicted and observed values. The models are statistically well-fitted. The areas under the ROC curves are .71 and .80 respectively, suggesting that they discriminate moderately well.

RASPBERRY BROWSE

For the RASPBERRY BROWSE class a total of two models were fit. The first model represented the case where RASPBERRY BROWSE was present at time 1 (RASPBERRY BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table B - 13. The second model represented the case where RASPBERRY BROWSE was not present at time 1 (RASPBERRY BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table B - 14. For both models all the variables are significant based on the Wald chi-square test at level α=0.05. For the RASPBERRY BROWSE – 1 the value for the Hosmer Lemeshow statistics is 13.0283 (p-values of 0.1109 with 8 degrees of freedom). For the RASPBERRY BROWSE – 0 model the value for the Hosmer Lemeshow statistic is 3.9777 (p-values of 0.8591 with 8 degrees of freedom). These p-values are large, exceeding the α=0.05 level so there is no evidence showing a disagreement between the predicted and observed values. The models are statistically well-fitted. The areas under the ROC curves are .75 and .76 respectively, suggesting that they discriminate moderately well.

BLUEBERRY BROWSE

For the BLUEBERRY BROWSE class a total of two models were fit. The first model represented the case where BLUEBERRY BROWSE was present at time 1 (BLUEBERRY BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table B - 15. The second model represented the case where BLUEBERRY BROWSE was not present at time 1 (BLUEBERRY BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table B - 16. For both models all the variables are significant based on the Wald chi-square test at level α=0.05. For the BLUEBERRY BROWSE – 1 the value for the Hosmer Lemeshow statistics is 13.0757 (p-values of 0.1093 with 8 degrees of freedom). For the BLUEBERRY BROWSE – 0 model the value for the Hosmer Lemeshow statistic is 15.8413 (p-values of 0.0447 with 8 degrees of freedom). These p-values equal or exceed the α=0.05 level so there is no strong evidence showing a disagreement between the predicted and observed values. The models are statistically well-fitted. The areas under the ROC curves are .80 and .77 respectively, suggesting that they discriminate moderately well.

ERICA BROWSE

For the ERICA BROWSE class a total of two models were fit. The first model represented the case where ERICA BROWSE was present at time 1 (ERICA BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table B - 17. The second model represented the case where ERICA BROWSE was not present at time 1 (ERICA BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table B - 18. For both models all the variables are significant based on the Wald chi-square test at level α=0.05. For the ERICA BROWSE – 1 the value for the Hosmer Lemeshow statistics is 8.1603 (p-values of 0.4180 with 8 degrees of freedom). For the ERICA BROWSE – 0 model the value for the Hosmer Lemeshow statistic is 6.6203 (p-values of 0.5781 with 8 degrees of freedom). These p-values are large, far exceeding the α=0.05 level so there is no strong evidence showing a disagreement between the predicted and observed values. The models are statistically well-fitted. The areas under the ROC curves are .78 and .79 respectively, suggesting that they discriminate moderately well.

HERB BROWSE

For the HERB BROWSE class a total of two models were fit. The first model represented the case where HERB BROWSE was present at time 1 (HERB BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table B - 19. The second model represented the case where HERB BROWSE was not present at time 1 (HERB BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table B - 20. For both models all the variables are significant based on the Wald chi-square test at level α=0.05. For the HERB BROWSE – 1 the value for the Hosmer Lemeshow statistics is 6.6203 (p-values of 0.5781 with 8 degrees of freedom). For the HERB BROWSE – 0 model the value for the Hosmer Lemeshow statistic is 13.7294 (p-values of 0.0891 with 8 degrees of freedom). These p-values exceed the α=0.05 level so there is no evidence showing a disagreement between the predicted and observed values. The models are statistically well-fitted. The areas under the ROC curves are .79 and .70 respectively, suggesting that they discriminate moderately well.

FERN BROWSE

For the FERN BROWSE class a total of two models were fit. The first model represented the case where FERN BROWSE was present at time 1 (FERN BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table B - 21. The second model represented the case where FERN BROWSE was not present at time 1 (FERN BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table B - 22. For both models all the variables are significant based on the Wald chi-square test at level α=0.05. For the FERN BROWSE – 1 the value for the Hosmer Lemeshow statistics is 7.6517 (p-values of 0.4682 with 8 degrees of freedom). For the FERN BROWSE – 0 model the value for the Hosmer Lemeshow statistic is 9.4160 (p-values of 0.3084 with 8 degrees of freedom). These p-values are large, far exceeding the α=0.05 level so there is no strong evidence showing a disagreement between the predicted and observed values. The models are statistically well-fitted. The areas under the ROC curves are .73 and .72 respectively, suggesting that they discriminate moderately well.

GRASS BROWSE

For the GRASS BROWSE class a total of two models were fit. The first model represented the case where GRASS BROWSE was present at time 1 (GRASS BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table B - 23. The second model represented the case where GRASS BROWSE was not present at time 1 (GRASS BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table B - 24. For both models all the variables are significant based on the Wald chi-square test at level α=0.05. For the GRASS BROWSE – 1 the value for the Hosmer Lemeshow statistics is 5.1275 (p-values of 0.7439 with 8 degrees of freedom). For the GRASS BROWSE – 0 model the value for the Hosmer Lemeshow statistic is 10.2307 (p-values of 0.2492 with 8 degrees of freedom). These p-values are large, far exceeding the α=0.05 level so there is no strong evidence showing a disagreement between the predicted and observed values. The models are statistically well-fitted. The areas under the ROC curves are .80 and .67 respectively, suggesting that the GRASS BROWSE – 1 class discriminates well and the GRASS BROWSE – 0 discriminates poorly.

4.2 Logarithmic Models

The logarithmic models work as the second step in the two step modelling process. The first step was to predict the probability of the given response variable being present or absent in the future. If the logistic model determined that a given response variable would be present at time 2, then a logarithmic model was needed to estimate in what quantity. For all the logarithmic models, the input datasets were the correctly classified observations of the matching logistic model.

Twenty eight models were fit to quantify the different response variables needed to predict the HSI parameters. The models can be divided into two categories, those estimating the percent share of the future growth classes and those estimating the percent share of the wildlife browse classes. Appendix C presents the tables containing the important parameters that are said to contribute in the prediction of the response variable, their associated estimated coefficient, their standard error and their probability for the t-statistic. Below each table is their estimated coefficient of multiple determination (R^2) and the number of observations used to fit the model. Example Tables are presented in the text for CONIFER BROWSE. Note, these example tables do not appear as the first example but rather maintain the original ordering. CONIFER BROWSE was selected as an example because it represented both the forest and wildlife disciplines. The fit statistics are summarised in Table 4-5.

4.2.1 Growth Classes

REGEN I

For REGEN I only one model was fit. The model represented the case where REGEN I was present at time 1 with trees in the overstory (REGEN I – 1 with trees). The parameters and the corresponding fit statistics are represented in Table C - 1. For the model all variables are significant based on the t-statistic at a α=0.05 level. For the REGEN I – 1 with trees model the R^2 = .54.

For the REGEN I – 1 no trees case, no sound model could be fit. Therefore for this case, in application, if the logistic model predicts that REGEN I will stay, the percent share of REGEN I from time 1 will represent the percent share of REGEN I at time 2.

For the REGEN I – 0 trees case, no sound model could be fit. Therefore for this case, in application, if the logistic model predicts that REGEN I will encroach, the average percent share of REGEN I from time 2 which is 6/10 or 60% will represent the percent share of REGEN I at time 2.

REGEN II

For REGEN II a total of 5 models were fit. The first model represented the case where REGEN II was present at time 1 with trees in the overstory (REGEN II – 1 with trees). The parameters and the corresponding fit statistics are represented in Table C - 2 .

The second model represented the case where REGEN II was present at time 1 and there were no trees in the overstory (REGEN II - 1 with no trees). The parameters and the corresponding fit statistics are represented in Table C - 3. The third model represented the case where REGEN II was not present at time 1 with trees in the overstory (REGEN II – 0 with trees). The parameters and the corresponding fit statistics are represented in Table C - 4. In all the models, all the variables are significant based on the t-test at a α=0.05 level. The respective R^2 values are .53, .57 and .77.

For the REGEN II – 0 no trees case, no sound model could be fit. Therefore for this case, in application, if the logistic model predicts that REGEN II will be present at time 2, two choices are available to assign the quantity. If there is REGEN I at time 1, the percent share of REGEN I at time 1 will be used for the REGEN II at time 2. For this case, it was found that in almost all cases, the percent share of REGEN II at time two was the same as the percent share of REGEN I at time 1. If there is no REGEN I at time 1, a quantity of 3/10 or 30% will be assigned. This is the average quantity or REGEN II at time 2, for the records in the database that represent this case.

Two additional quantitative models were fit, the REGEN II – larch and REGEN II – broadleaved. The parameters and the corresponding fit statistics are represented in Table C - 5 and Table C - 6 respectively. In the two models, all the variables are significant based on the t-test at a α=0.05 level. The respective R^2 values are .71 and .68.

4.2.2 Wildlife Browse Classes

NO BROWSE

For the NO BROWSE class a total of two models were fit. The first model represented the case where NO BROWSE was present at time 1 (NO BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table C - 7. The second model represented the case where NO BROWSE was not present at time 1 (NO BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table C - 8. For both models all the variables are significant based on the t-test at a α=0.05 level. The respective R^2 values are .69 and .63 .

CONIFER BROWSE

For the CONIFER BROWSE class a total of two models were fit. The first model represented the case where CONIFER BROWSE was present at time 1 (CONIFER BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table 4-3. The second model represented the case where CONIFER BROWSE was not present at time 1 (CONIFER BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table 4-4. For both models all the variables are significant based on the t-test at a α=0.05 level. The respective R^2 values are .61 and .49 .

Table 4-3: Logarithmic regression for Conifer Browse – 1. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle 4-3: Logarithmische Regression für Nadelbäume – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	3.20214	0.08174	<.0001
SQRT(A_NDSH_T1)	Conifer Browse	0.50580	0.01781	<.0001
SQRT(A_NOSH_T1)	No Browse	-0.21965	0.01143	<.0001
INTVAL	Interval Value	-0.50077	0.01243	<.0001
STD1_T2	Norway Spruce	-0.14468	0.01327	<.0001
GZD10	Growth Zone 10	-0.05683	0.02233	0.0110
GZD12,17	Growth Zone 12 or 17	0.10467	0.02064	<.0001
GZD18	Growth Zone 18	0.17294	0.02286	<.0001
SCD3	Soil Group 3	0.04727	0.02197	0.0315
SCD4,17,18	Soil Group 4, 17 or 18	0.16877	0.01414	<.0001
SCD6	Soil Group 6	0.33945	0.04282	<.0001
SCD19	Soil Group 19	0.09211	0.02573	0.0003
GVD1	Shade Herb Type	-0.23746	0.02616	<.0001
C_BA	Change in Basal Area	-0.00678	0.00072830	<.0001
JUNGIISH_T1	Regen II	-0.02779	0.00170	<.0001
[3]*OVERSH_T2*	Sum of Overstory Growth Classes	-0.03581	0.00193	<.0001

R^2=.61
n = 4323

[3] OVERSH_T2 = STANGSH_T2 + BHISH_T2 + BHIISH_T2

Table 4-4: Logarithmic regression for Conifer Browse – 0. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle 4-4: Logarithmische Regression für Nadelbäume – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	0.20675	0.03161	<.0001
SQRT(A_NOSH_T1)	No Browse	-0.11839	0.00358	<.0001
ELEV	Elevation	0.00715	0.00069470	<.0001
INTVAL	Interval Value	0.06555	0.00507	<.0001
GZD11,12	Growth Zone 11 or 12	0.06062	0.00928	<.0001
GZD18	Growth Zone 18	0.22879	0.01241	<.0001
GZD20	Growth Zone 20	0.06715	0.01121	<.0001
STD0_T2	No Trees in Angle Count	0.48052	0.01366	<.0001
GVD1	Shade Herb Types	-0.09340	0.00678	<.0001
GVD6,16,18	Sparse Moss, Pasture Forest Types or Seep Vegetation Types	0.10974	0.00688	<.0001
GVD10	*Calluna* Type	0.24954	0.07897	0.0016
JUNGIISH_T1	Regen II	-0.01148	0.00119	<.0001
[4]*OVERSH_T2*	Sum of Overstory Growth Classes	-0.02635	0.00128	<.0001

R^2=.49
n = 7893

Deciduous Browse

For the Deciduous Browse class a total of two models were fit. The first model represented the case where Deciduous Browse was present at time 1 (Deciduous Browse – 1). The parameters and the corresponding fit statistics are represented in Table C - 9. The second model represented the case where Deciduous Browse was not present at time 1 (Deciduous Browse - 0). The parameters and the corresponding fit statistics are represented in Table C - 10. For both models all the variables are significant based on the t-test at a α=0.05 level. The respective R^2 values are .65 and .50.

[4] OVERSH_T2 = STANGSH_T2 + BHISH_T2 + BHIISH_T2 + STARKSH_T2

SHRUB BROWSE

For the SHRUB BROWSE class a total of two models were fit. The first model represented the case where SHRUB BROWSE was present at time 1 (SHRUB BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table C - 11. The second model represented the case where SHRUB BROWSE was not present at time 1 (SHRUB BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table C - 12. For both models all the variables are significant based on the t-test at a α=0.05 level. The respective R^2 values are .67 and .38 .

RASPBERRY BROWSE

For the RASPBERRY BROWSE class a total of two models were fit. The first model represented the case where RASPBERRY BROWSE was present at time 1 (RASPBERRY BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table C - 13. The second model represented the case where RASPBERRY BROWSE was not present at time 1 (RASPBERRY BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table C - 14. For both models all the variables are significant based on the t-test at a α=0.05 level. The respective R^2 values are .69 and .41 .

BLUEBERRY BROWSE

For the BLUEBERRY BROWSE class a total of two models were fit. The first model represented the case where BLUEBERRY BROWSE was present at time 1 (BLUEBERRY BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table C - 15. The second model represented the case where BLUEBERRY BROWSE was not present at time 1 (BLUEBERRY BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table C - 16. For both models all the variables are significant based on the t-test at a α=0.05 level. The respective R^2 values are .74 and .44.

ERICA BROWSE

For the ERICA BROWSE class only one model was fit. The model represented the case where ERICA BROWSE was present at time 1 (ERICA BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table C - 17. For the model all the variables are significant based on the t-test at a α=0.05 level. The respective R^2 value is .80.

For the ERICA BROWSE – 0 case, no sound model could be fit. For this case, in application, if the logistic model predicts that *ERICA* will be present at time 2, a quantity of 2 or 20% will be assigned. This is the average quantity for the records in the database that represent this case.

HERB BROWSE

For the HERB BROWSE class a total of two models were fit. The first model represented the case where HERB BROWSE was present at time 1 (HERB BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table C - 18. The second model represented the case where HERB BROWSE was not present at time 1 (HERB BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table C - 19. For both models all the variables are significant based on the t-test at a α=0.05 level. The respective R^2 values are .61 and .58.

FERN BROWSE

For the FERN BROWSE class a total of two models were fit. The first model represented the case where FERN BROWSE was present at time 1 (FERN BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table C - 20. The second model represented the case where FERN BROWSE was not present at time 1 (FERN BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table C - 21. For both models all the variables are significant based on the t-test at a α=0.05 level. The respective R^2 values are .70 and .37 .

GRASS BROWSE

For the GRASS BROWSE class a total of two models were fit. The first model represented the case where GRASS BROWSE was present at time 1 (GRASS BROWSE – 1). The parameters and the corresponding fit statistics are represented in Table C - 22. The second model represented the case where GRASS BROWSE was not present at time 1 (GRASS BROWSE - 0). The parameters and the corresponding fit statistics are represented in Table C - 23. For both models all the variables are significant based on the t-test at a α=0.05 level. The respective R^2 values are .70 and .53.

4.3 Overall Performance

For each model pair, where appropriate, the efficiency of both models according to the equation in the methods section (3.5) was determined. In Table 4-5 the calculated efficiency results along with a summary of the results for the individual logistic and logarithmic models are presented. In

Figure 4-1, Figure 4-2, Figure 4-3, Figure 4-3, Figure 4-5, and Figure 4-6 the results of the observed versus the predicted distributions for all the models are presented.

Table 4-5: Summary of the logistic, logarithmic and total efficiency fit statistics for each of the plot descriptors modelled. For logistic models, the p-value for the Hosmer-Lemeshow test statistic (calculated using an equal number of observations per group) and the area under the receiver operating characteristics curve are presented. For the logarithmic regression the coefficient of determination is presented. Total model performance is tested using the efficiency statistic.

Tabelle 4-5: Übersicht über die logistische, logarithmische und gesamte Anpassungsgüte für alle modellierten Parameter. Für logistische Modelle werden die Irrtumswahrscheinlichkeit des Hosmer & und Lemeshow Tests (für Klassen gleicher Häufigkeit) und die Flächen unter der „Receiver Operating Characteristic" Kurve angegeben. Für die logarithmische Regression wird das Bestimmtheitsmaß angegeben. Die gesamte Anpassungsgüte wird durch die „Efficiency statistic" characterisiert.

Plot Descriptor Class	**Plot Descriptor**	**Logistic Regression**		**Logarithmic Regression**	**Total Efficiency**
		p-value Hosmer-Lemeshow	**Area Under ROC Curve**	**R^2**	**EF**
Growth Class	REGEN I – 1 TREES	.18	.76	.54	-.08
	REGEN I – 1 NO TREES	.26	.77	N/A	N/A
	REGEN II – 1 TREES	.41	.76	.53	.16
	REGEN II – 1 NO TREES	.45	.72	.57	.13
	REGEN II – 0 TREES	.93	.79	.77	.04
	REGEN II – 0 NO TREES	.13	.85	N/A	N/A
	REGEN II – BROADLEAVED	N/A	N/A	.71	N/A
	REGEN II – LARCH	N/A	N/A	.68	N/A
Wildlife	NO BROWSE – 1	.68	.83	.69	.34
	NO BROWSE – 0	.12	.73	.63	.16
	CONIFER BROWSE – 1	.62	.74	.61	.13
	CONIFER BROWSE – 0	.15	.73	.49	.07
	DECIDUOUS BROWSE – 1	.60	.70	.65	.08
	DECIDUOUS BROWSE – 0	.91	.78	.50	-.07
	SHRUB BROWSE – 1	.66	.71	.67	.12
	SHRUB BROWSE – 0	.08	.80	.38	0
	RASPBERRY BROWSE – 1	.11	.75	.69	.25
	RASPBERRY BROWSE – 0	.86	.76	.41	-.10
	BLUEBERRY BROWSE – 1	.11	.80	.74	.47
	BLUEBERRY BROWSE – 0	.05	.77	.44	-.09
	ERICA BROWSE – 1	.42	.78	.80	.43
	ERICA BROWSE – 0	.42	.79	N/A	N/A
	HERB BROWSE – 1	.58	.79	.61	.27
	HERB BROWSE – 0	.09	.70	.58	-.10
	FERN BROWSE – 1	.47	.73	.70	.10
	FERN BROWSE – 0	.31	.72	.37	-.07
	GRASS BROWSE – 1	.75	.80	.70	.32
	GRASS BROWSE – 0	.25	.67	.53	-.07

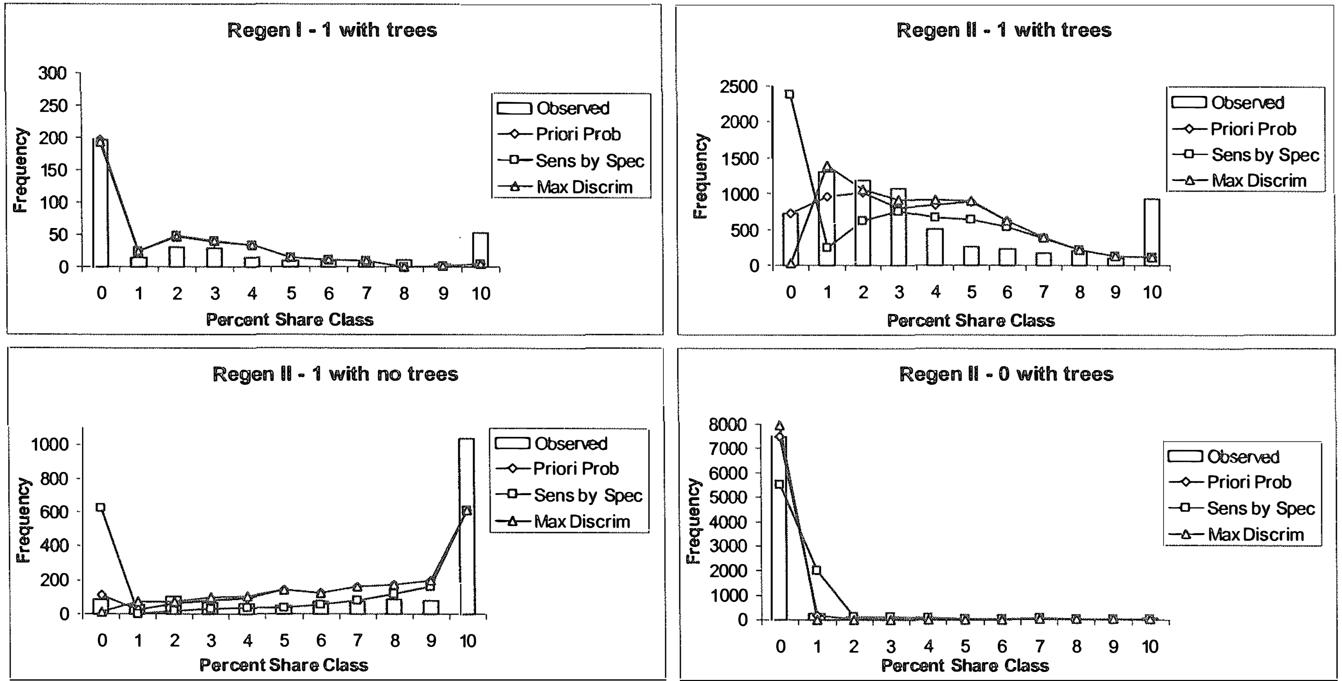


Figure 4-1: The predicted versus the observed distributions, for the cutoff probabilities defined by the probability where the predicted distribution matches the a priori probability (Priori Prob), where sensitivity and specificity, both together are maximised (Sens by Spec) and where maximum discrimination is obtained (Max Discrim) for the Regen I and Regen II growth classes.

Abbildung 4-1: Verteilung der geschätzten Werte über den beobachteten Werten für einen Schwellenwert, bei dem (i) die Verteilung der geschätzten Werte der a priori Wahrscheinlichkeit der beobachteten Werte entspricht, für (ii) maximale Sensitivität, (iii) maximale und Spezifität, und (iv) maximale Summe aus Spezifität und Sensitivitäe, und (v) maximale Diskriminierung zwischen den Gruppen, für die Wuchsklassen, Verjüngung I (REGEN I) und Verjüngung II (REGEN II).

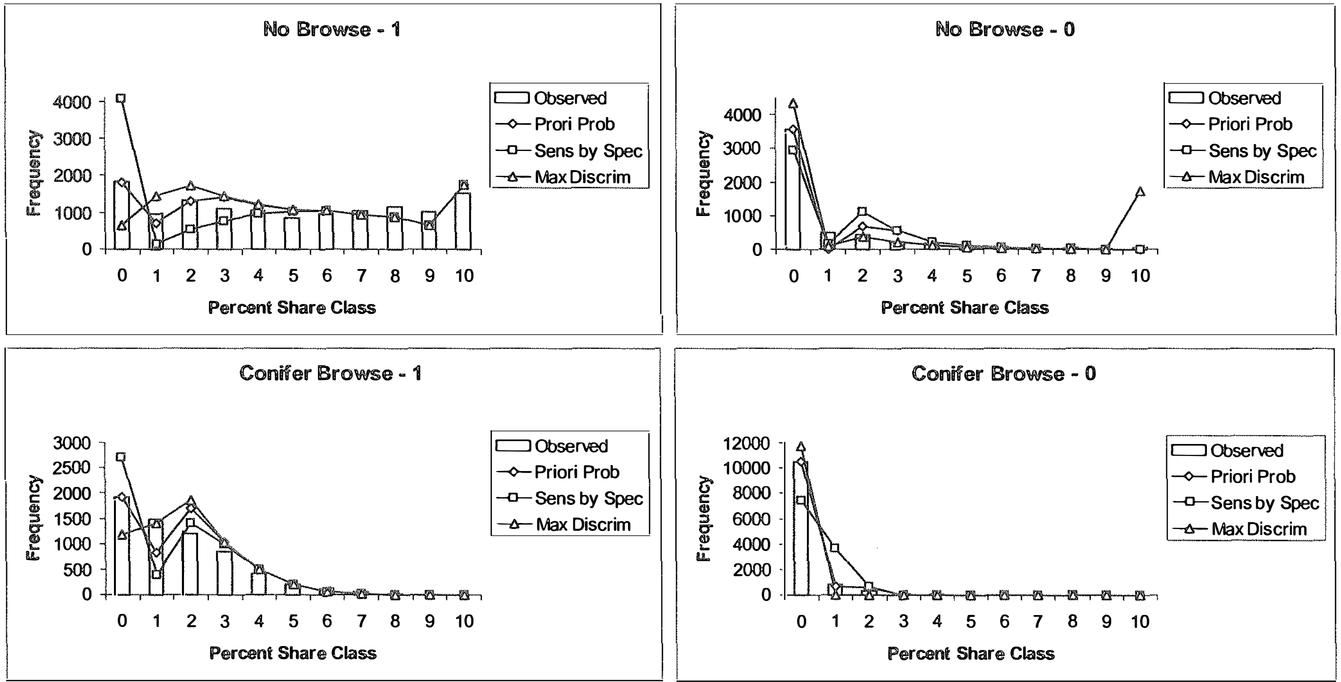


Figure 4-2 : The predicted versus the observed distributions, for the cutoff probabilities defined by the probability where the predicted distribution matches the a priori probability (Priori Prob), where sensitivity and specificity, both together are maximised (Sens by Spec) and where maximum discrimination is obtained (Max Discrim) for the No Browse and Conifer Browse classes.

Abbildung 4-2: Verteilung der geschätzten Werte über den beobachteten Werten für einen Schwellenwert, bei dem (i) die Verteilung der geschätzten Werte der a priori Wahrscheinlichkeit der beobachteten Werte entspricht, für (ii) maximale Sensitivität, (iii) maximale und Spezifität, und (iv) maximale Summe aus Spezifität und Sensitivitäe, und (v) maximale Dislcriminierung zwischen den Gruppen, für die Wildäsungtypen Keine Äsung und Nadelbäume.

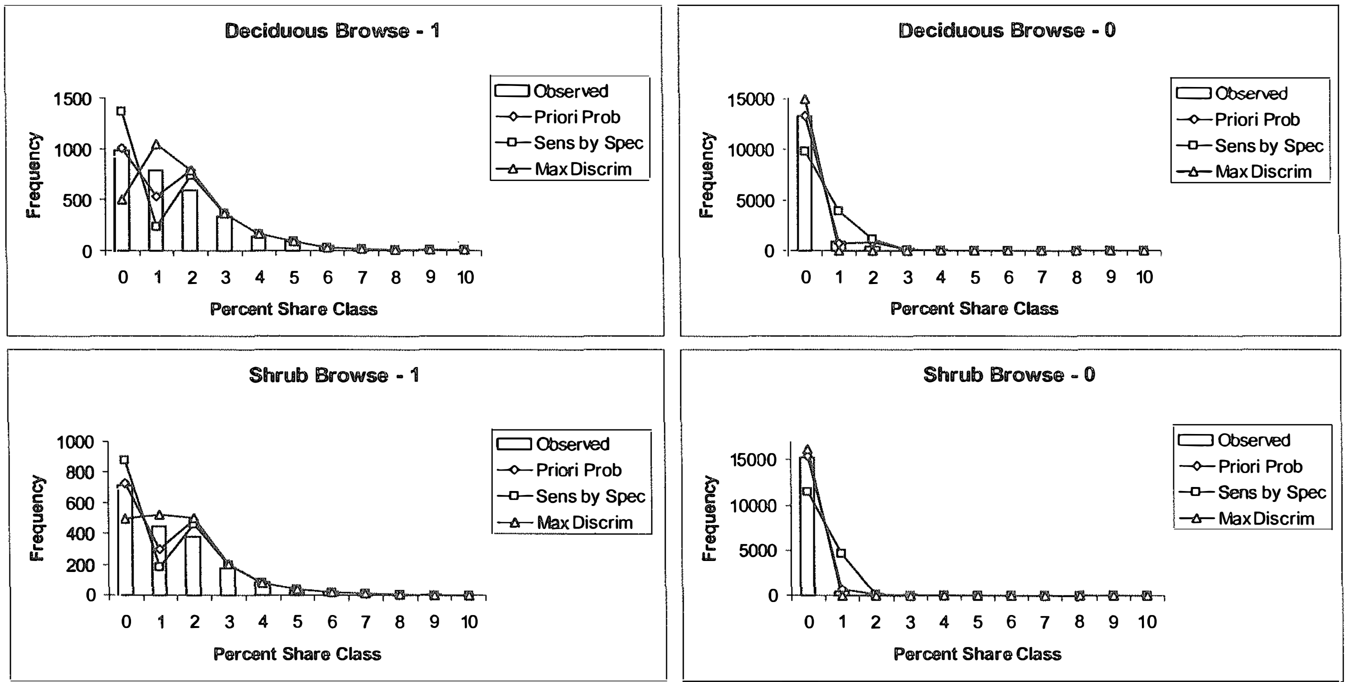


Figure 4-3 : The predicted versus the observed distributions, for the cutoff probabilities defined by the probability where the predicted distribution matches the a priori probability (Priori Prob), where sensitivity and specificity, both together are maximised (Sens by Spec) and where maximum discrimination is obtained (Max Discrim), for the Deciduous and Shrub Browse classes.

Abbildung 4-3: Verteilung der geschätzten Werte über den beobachteten Werten für einen Schwellenwert, bei dem (i) die Verteilung der geschätzten Werte der a priori Wahrscheinlichkeit der beobachteten Werte entspricht, für (ii) maximale Sensitivität, (iii) maximale und Spezifität, und (iv) maximale Summe aus Spezifität und Sensitivitäe, und (v) maximale Diskriminierung zwischen den Gruppen, , für die Wildäsungtypen Laubbäume und Sträucher.

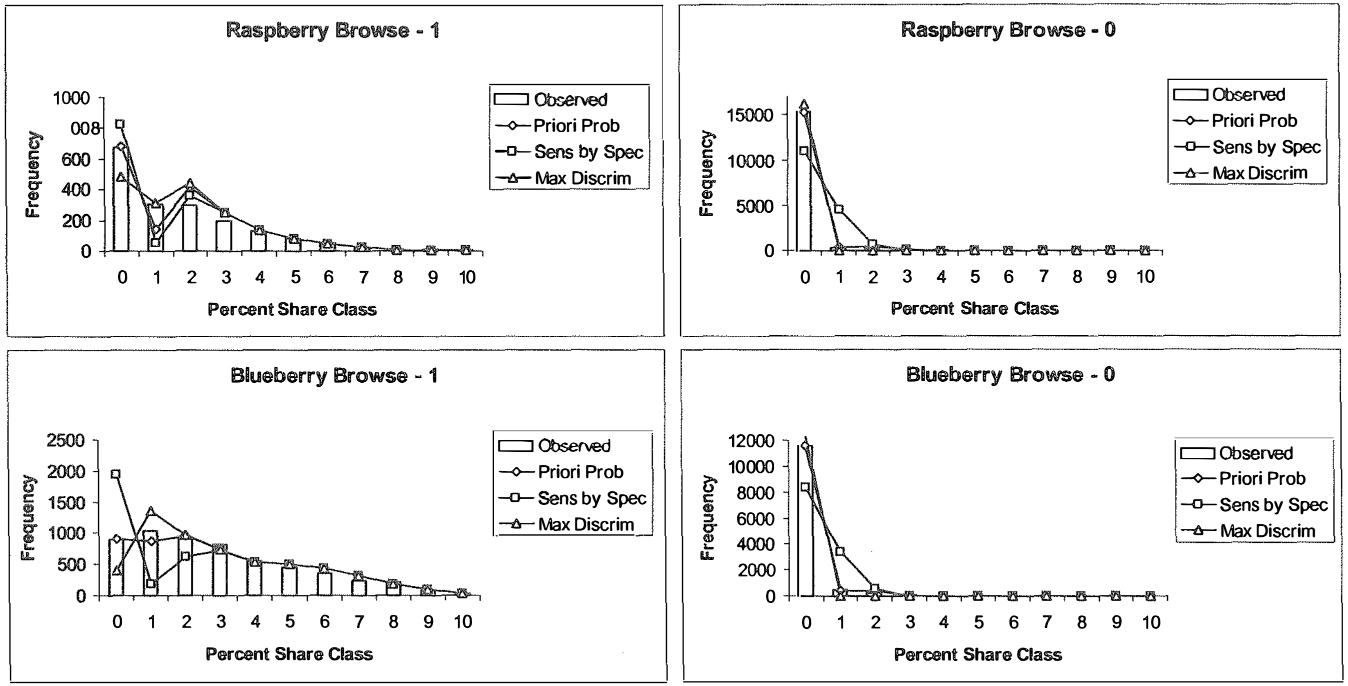
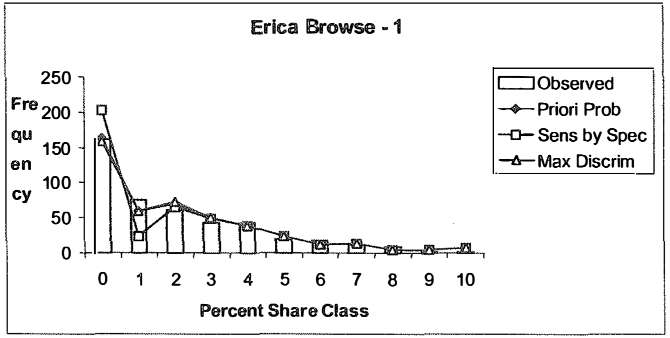


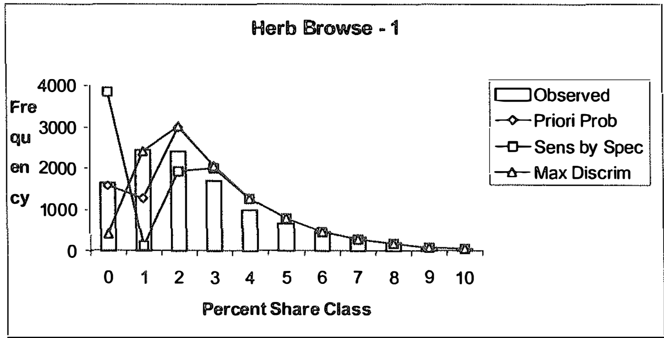
Figure 4-4: The predicted versus the observed distributions, for the cutoff probabilities defined by the probability where the predicted distribution matches the a priori probability (Priori Prob), where sensitivity and specificity, both together are maximised (Sens by Spec) and where maximum discrimination is obtained (Max Discrim), for the Raspberry and Blueberry Browse classes.

Abbildung 4-4: Verteilung der geschätzten Werte über den beobachteten Werten für einen Schwellenwert, bei dem (i) die Verteilung der geschätzten Werte der a priori Wahrscheinlichkeit der beobachteten Werte entspricht, für (ii) maximale Sensitivität, (iii) maximale und Spezifität, und (iv) maximale Summe aus Spezifität und Sensitivitäe, und (v) maximale Diskriminierung zwischen den Gruppen, für die Wildäsungtypen Himbeere und Heidelbeere.



No Logarithmic model for

Erica Browse - 0



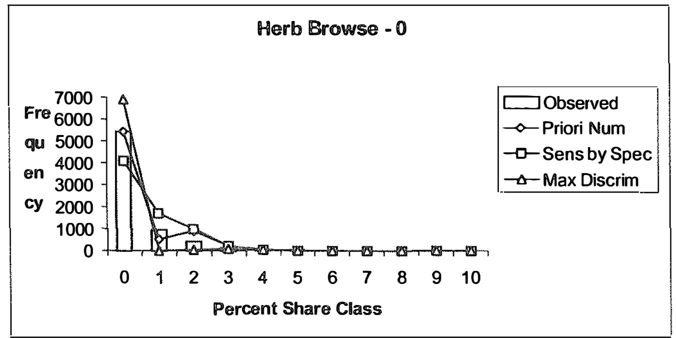


Figure 4-5: The predicted versus the observed distributions, for the cutoff probabilities defined by the probability where the predicted distribution matches the a priori probability (Priori Prob), where sensitivity and specificity, both together are maximised (Sens by Spec) and where maximum discrimination is obtained (Max Discrim), for the Erica and Herb Bowse classes.

Abbildung 4-5: Verteilung der geschätzten Werte über den beobachteten Werten für einen Schwellenwert, bei dem (i) die Verteilung der geschätzten Werte der a priori Wahrscheinlichkeit der beobachteten Werte entspricht, für (ii) maximale Sensitivität, (iii) maximale und Spezifität, und (iv) maximale Sunnne aus Spezifität und Sensitivitäe, und (v) maximale Diskriminierung zwischen den Gruppen, , für die Wildäsungtypen Erika und Kräuter.

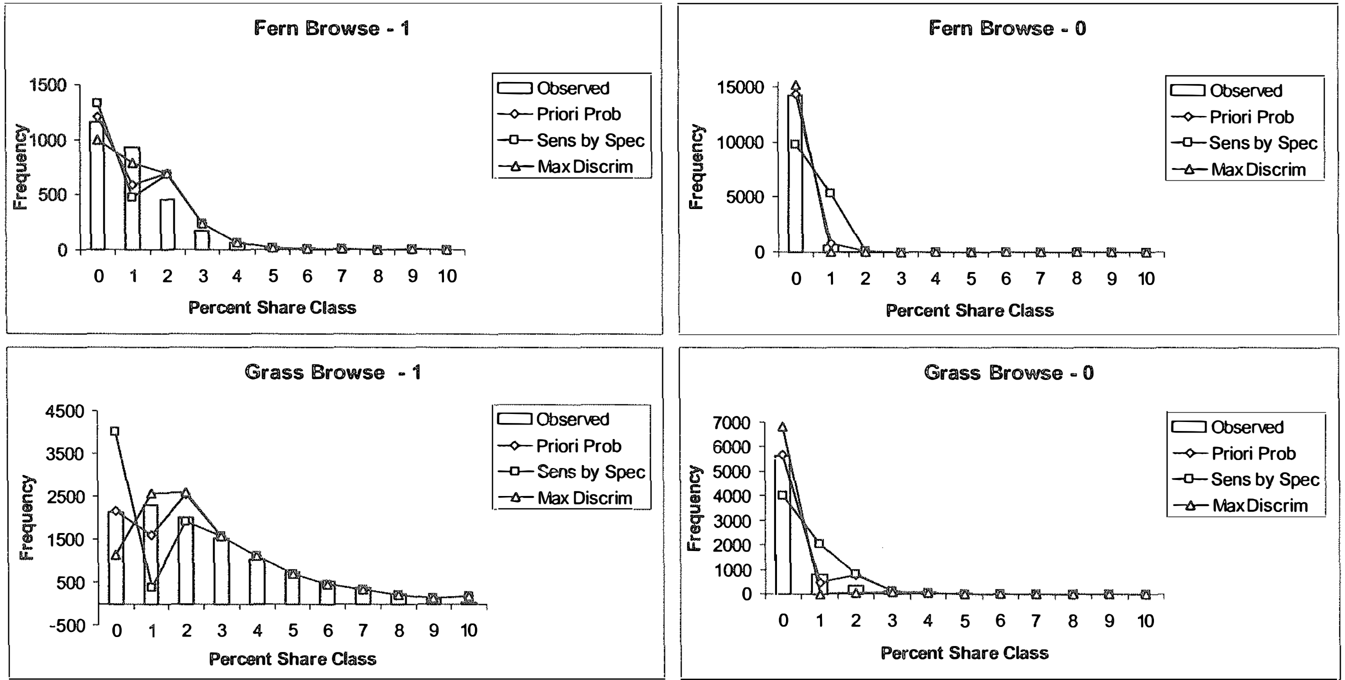


Figure 4-6: The predicted versus the observed distributions, for the cutoff probabilities defined by the probability where the predicted distribution matches the a priori probability (Priori Prob), where sensitivity and specificity, both together are maximised (Sens by Spec) and where maximum discrimination is obtained (Max Discrim), for the Fern and Grass Browse classes.

Abbildung 4-6: Verteilung der geschätzten Werte über den beobachteten Werten für einen Schwellenwert, bei dem (i) die Verteilung der geschätzten Werte der a priori Wahrscheinlichkeit der beobachteten Werte entspricht, für (ii) maximale Sensitivität, (iii) maximale und Spezifität, und (iv) maximale Summe aus Spezifität und Sensitivitäe, und (v) maximale Diskriminierung zwischen den Gruppen, für die Wildäsungtypen Farne und Gräser.

5 DISCUSSION

The prediction of future probabilities and quantities of the growth classes and wildlife browse classes are based on two separate assumptions concerning the dynamics over time. The growth classes represent transitional stages of stand succession. One would expect a stand to progress from a clearing (after a clearcut) or to release (after a thinning) to REGEN I to REGEN II to POLE and so on. Wildlife browse classes on the other hand, do not grow out of a class, with the exception of CONIFER and DECIDUOUS BROWSE. If they are present on a site at time 1, they can only change their state, either by increasing or decreasing their prominence or by disappearing entirely. If they are not on a site at time 1, they can either encroach onto the site or continue to not be on the site.

What is consistent between both growth classes and wildlife browse classes is the significance of their presence/absence at time 1. The biological/man caused processes which dictate a growth class or wildlife browse class disappearing from a site, when it is already present, can be significantly different than those that stimulate its encroachment onto a site. What was proposed at the beginning of this study was to take advantage of the status of the response variable at time 1 and to utilise stand information from both time 1 and time 2.

The status of the response variable at time 1, represented by its percent share, was tested in all the models. Because the models were split into "present at time 1" (- 1 case) and "not present at time 1" (- 0 case), the status at time 1 was only applicable in the "present at time 1" case. As expected, of the 27 models developed for the "present at time 1" case (both logistic and logarithmic, excluding the larch and broadleaved models), 23 included the state of the response variable at time 1. This makes intuitive sense since the 5/6 year difference between remeasurements is not long enough for drastic changes in stand composition, such that one would not expect species to entirely disappear in this short time frame. At the beginning of the study, it was posed that status of the response variable at time 1 was important in predicting the time 2 status. Its inclusion in so many models supports this. Furthermore, in all the cases where it did appear in the model, the variable was dominant in the model.

The cases where the status of the response variable at time 1 was not important, was surprisingly, in the logistic REGEN I, with and without trees and the CONIFEROUS BROWSE and ERICA BROWSE classes. In the case of REGEN I with and without trees, the absence of the status at time 1 in the models, shows that it is not the abundance of REGEN I at time 1 that dictates whether it will be there at time 2, but rather the site and stand conditions. In the "with trees" case, this suggests that in terms of competition, intra-specific competition is not as an important factor as competition from above. For this case the notable variables are stand structure, quadratic mean diameter and the density of the pole stand above. In the "without trees" case the important variables are elevation, relief, the dummy variable for spruce and the percent area of NO BROWSE. The NO BROWSE variable is an interesting and important variable in this and in many other models. NO BROWSE describes, how much of the region between the forest floor and 1.5 meters, has no browsable species. For there to be NO BROWSE, the density of the stand above must be high enough to limit the amount of light reaching the forest floor. This would suggest that the NO BROWSE class is a measure of overstory density. However there are two cases where this would not apply, when a forested area has been recently clear cut and encroachment of vegetation has not yet occurred, or when the height of the regeneration is low offering little browse. In both of these cases this situation would only last for a short period. In the case of the REGEN I model with no trees, the fact that the NO BROWSE variable was in the model before the percent share of REGEN I at time 1, indicates that the NO BROWSE variable measures the height of the REGEN I at time I. This height dictates whether or not REGEN I will be present or not at time 2.

The role of the NO BROWSE class within all the models is very evident. It is present in 29 of the 49 models. There are 3 definite roles that NO BROWSE played in the models. The most obvious observation is that the NO BROWSE variable has entered all of the models that the response variable is "not present at time 1" (- 0 case), with the exception of BLUEBERRY and the NO BROWSE case. Its coefficient was always negative. This indicates clearly that for a species to encroach onto a site, the canopy above must be open enough to let light reach the forest floor and that the NO BROWSE variable is a measure of this density. The second observation is that for the BLUEBERRY, ERICA, HERB, FERN and GRASS BROWSE classes, when the response variable was present at time 1 (- 1 case), the NO BROWSE variable was never in the models. This suggests that in these cases, the percent share of the response variable at time 1, indirectly represented the density of the forest stand above. The third observation was, that this was not true for the

CONIFER, DECIDUOUS, SHRUB and the RASPBERRY BROWSE classes. In these cases both the status of the response variable at time 1 and the NO BROWSE variable were present in the models, indicating that both variables were offering different information. The concern was then, were these variables independent? In the logarithmic regressions, the two variables were considered independent based on their variance inflation factors. In logistic regression there is no simple method to test for independence, so the independence demonstrated in the logarithmic models was assumed to apply to the logistic models. This is not an unreasonable assumption since both modelling strategies are a form of regression.

The other objective of this study was to use overstory information from both time 1 and time 2. This desire was based on the fact that changes, such as harvesting and thinning are not represented when only data from time 1 or time 2 are used. Knowing that a growth model, in application, can provide useful information of the future forest stand, including species composition, density and vertical structure; made it possible to test whether information from both times was truly useful. In order to do this the same variables from time 1 and time 2 were tested. At the beginning of the modelling process, using stepwise regression, it was seen that variables such as stand type (species composition), stand structure and stand density from time 2 entered the models before or at the same time as the same variables from time 1. This meant that information from time 2 was as much as or more useful in predicting the time 2 response variables, when compared to the time 1 variable. Most importantly this meant that the models would be sensitive to changes in stand structure. Practically, the models could be applied in areas where significant changes in stands where being actively pursued, like in the case of restoration. Models developed using only data from time 1, would lack the ability to react to these changes. Because of the strength of the time 2 overstory structure variables in the testing stage, in the final model fitting stages, they were chosen over time 1 variables.

Reviewing the final logistic and logarithmic models, several observations could be made about the variables used from time 2. The most obvious variable was the change in basal area (*C_BA*) which appeared in 23 of the 49 models (excluding the larch and broadleaved models). The *C_BA* variable is the basal area from time 2 minus the basal area from time 1. This is a variable that uses both time 1 and time 2 data. A positive basal area that is near zero represents normal stand growth. A large positive basal area is most likely caused by using the angle count method as discussed in the methods section. If the *C_BA* variable is negative, it suggests stem removal. The larger the negative value, the more stems removed. The cases represented by the *C_BA* variable was what was expected to be the case and hoped for. The desire was for the models to respond to marked changes in the stand structure, assuming that in these cases, the understory vegetation changes would be the greatest. In the models developed, the *C_BA* variable coefficient is both positive and negative depending on whether harvesting and thinning of a stand favours the response variable or not. In section (5.2) which discusses the interpretation of the coefficients, the interpretation of the *C_BA* variable for each model is presented.

Although the *C_BA* variable was a dominant variable, there are other variables from time 2 that occur in place of or together with the *C_BA* variable. These are the change in quadratic mean diameter (*C_QMD*), the quadratic mean diameter at time 2 (*QMD_T2*) and the crown competition factor at time 2 (*CCF_T2*). In 32 out of the 46 models (those with trees, excluding the larch and broadleaved models), at least one of these variables *C_BA*, *C_QMD*, *QMD_T2*, or *CCF_T2* are in the models.

Other variables representing time 2 include, the percent share of the overstory growth classes (*STANGSH_T2*, *BHISH_T2*, *BHIISH_T2* and *STARKSH_T2*), the species composition (*STD0_T2 - STD41_T2*) and the stand structure (*SSD1_T2, SSD2_T2* and *SSD3_T2*). Their significance is that they represent the stand structure at time 2, after all changes, including normal growth, have already taken place.

5.1 Model Performance

The evaluation of model performance is ideally done on an independent dataset. Such a dataset was in the data collection phase at the time of this writing and in the future is expected to provide an excellent base for the evaluation of the models developed. In the absence of this dataset, there is still value in assessing the models' performance based on the data used.

For the logistic models, these include the fit statistics from the Hosmer and Lemeshow test and the area under the receiver operating characteristics (ROC) curve. From Table 4-5 the p-values for the Hosmer and Lemeshow test statistic, $\hat{C}$, calculated using the equal number of observations per group method, show that all the models meet the α=0.05 level. This indicates that there is no evidence to suggest that there is disagreement between the observed and predicted values. In most cases the p-values far exceed the threshold of $\alpha=0.05$.

The area under the ROC curve measures a logistic model's ability to discriminate. The important fact is that this measure is both independent of species prevalence and the decision threshold or cutoff probability. Areas of 0.5 to 0.7 indicate poor discrimination, 0.7 to 0.8 indicate moderate discrimination, values from 0.8 to 0.9 indicate good discrimination and values higher than 0.9, indicate excellent discrimination. From Table 4-5 the majority of the ROC areas for the logistic models developed are above 0.7. The only exception is Grass – 0 with a ROC area of .67 which is slightly below 0.7. The results of the ROC curve areas suggest that all the models provide acceptable discrimination.

For the logarithmic regression model, the most common measure of performance is the coefficient of multiple determination or R^2. It measures the amount of variation that is explained by the regression. One should be reminded that the dataset used to fit the logarithmic models comes from those observations which were correctly predicted by the matching or paired logistic model. From Table 4-5 the R^2 values vary from .37 to .80. As expected, the R^2 values for the models representing the "not present at time 1" (- 0 case) are all significantly lower than the "present at time 1" (- 1 case). This is because the "not present at time 1" (- 0) case, represents the "rest" of the data which is expected to be highly variable. Huisman et al. (1993), observed that in vegetation modelling, many species will show considerable variation around the observed response. In addition to this, the response variables in this study are only ocular estimates with a coarse measurement resolution (tenths). Because of this, the response variables are expected to possess notable measurement or classification error. For these reasons, the R^2 values obtained from the models developed appear to be reasonable.

Although both the logistic and the logarithmic models show reasonable fit statistics, they are most likely not independent, since the data used to develop the logarithmic models are the „*correctly predicted*" observations from the logistic model. The support for using this methodology is provided in section (3.4). The lack of independence of the two models suggests that each model pair must be evaluated together. To do this, the efficiency statistic (EF) was used, which compares the predicted quantities to the observed. An EF value of 0 suggests that the model is no better than the average, an EF value nearing 1 suggests an efficient model, a negative EF value suggests that the model is biased. From Table 4-5, the EF values vary considerably. Seven are negative with values ranging from 0 to -0.1 suggesting that they are marginally biased. Of these, six are the "not present at time 1" (- 0) case. The remainder of the models have positive EF values, ranging from 0 to 0.47 which suggests that they are better than the mean.

The presentation of the EF statistics was done to provide the reader with some idea of overall performance. However, there are several factors that are important to recognise. Firstly, this evaluation was not done on an independent dataset, so the results should be better than on an independent dataset. Secondly, the reader must acknowledge that the predictions are based on two models, which in both cases have notable error. Thirdly, the EF values compare the performance of observed versus predicted outcomes at a subplot level. This means that a predicted value of 30% for blueberry at time 2 is considered different than an observed value of 20%. In reality one would have to question whether this is a significant difference. Reviewing the data collection procedures for the development of the HSI models, the BEGG and BEVJ HSI parameters for example, are measured in 7 classes; 0 (0%), 1(- 5%), 2(6-10%), 3(11-20%), 4(21-30%), 5(31-50%), 6(51-75%) and 7(76-100%). Other HSI parameters were measured in similar classes. The point is, that the EF measure is a precision measure and in this case is far more stringent than is required in terms of application. Notably, the classes listed above are not evenly distributed but rather show an emphasis in the lower classes. Another aspect which relates to applicability, deals with the spatial arrangement of the vegetation. Referring back to the blueberry example above, the comparison of observed versus predicted is at a subplot level, the "exact" same subplot. In wildlife management, management is on large areas for roe deer, larger than 100 ha according to Reimoser & Zandl (1994). This suggests that having the exact observed versus predicted values spatially, is of less importance than correctly predicting the average over the entire management area. Relating this to forestry, when modelling mortality, it is not as important to know which tree dies, but how many trees within each size class in the stand die. This further makes the EF measure over stringent.

The concept of management of large areas then suggests that a reasonable method to evaluate the performance of a model, is to use the frequency distribution of each percent share class. If the predicted distribution is similar to the observed, regardless of the spatial arrangement, a good portion of the requirement for wildlife management is met. This is not intended to insinuate that the spatial arrangement is not important, it is intended to point out that obtaining the correct frequency distribution is a requirement. To obtain the frequency distribution of the percent share classes, using a two model system, there is still the requirement of choosing a cutoff value in logistic regression. This cutoff value ultimately determines which observations will be present at time 2, thus requiring quantification. In the model development stage, the a priori probability was chosen as the cutoff point to select the *„correctly predicted"* observations needed to construct the input dataset for the logarithmic model development. The choice to use the a priori probability again in the application stage is challenged by two other theoretically feasible cutoff points: 1) at the probability where the sensitivity and the specificity together, are both maximised; and 2) at the probability where the maximum discrimination is obtained. The answer was not intuitively clear. The importance of obtaining the correct frequency distribution warranted that this decision be made carefully. To make the choice, outcomes of the two model system using the 3 different logistic regression cutoff points were predicted. The frequency distribution for each of the 3 cases was then plotted against the observed frequency distribution. After a preliminary review of the plots, it was clear that the a priori probability provided a very poor distribution between observed and predicted observations and was therefore not appropriate. It was more intuitive to choose a cutoff value that represented the a priori probability within the predicted data (where the ratio, between those observations predicted to be present in the future over the total number of observations, was the same as the a priori probability). This revised definition of a priori probability became the new cutoff value tested. The results for each model pair are presented in Figure 4-1, Figure 4-2, Figure 4-3, Figure 4-4, Figure 4-5 and Figure 4-6. For the browse classes, it was immediately clear that the redefined a priori probability provided the nearest predicted frequency distribution to the observed frequency distribution. The zero class was predicted very closely to the observed in all cases. This is expected since, the redefined a priori probability defines explicitly the number of zeros and ones. The problems appeared to be with the 1 and 2 classes. However as discussed earlier, the difference between 10% and 20% is not critical. The plots clearly show that the sensitivity by the specificity cutoff and the maximum discrimination, both are very unpredictable especially in the first 3 percent share classes. From these plots it was clear that the "best" choice for the cutoff was the redefined a priori probability. This was a surprising result with an important implication. In the literature, the pros and cons in the selection of different cutoff probabilities for logistic models is often discussed. Many authors suggest the use of the a priori probability as a cutoff value when modelling vegetation, however in this study this was clearly not a good choice. For the browse classes, the redefined a priori probability was the best choice.

The distributional results for the growth classes are not as clear as for the browse classes as seen in Figure 4-1. The zero class was predicted very closely to the observed for all the growth class cases. As with the browse classes, this is expected, since the a priori probability defines explicitly the number of zeros and ones. This is an important result. However, after this, the models have difficulty in matching the observed distribution. In the REGEN I - 1 with trees and the REGEN II - 1, with and without trees, the most obvious departure from the observed is in the last class. In these three cases, the predictions underestimate the observed. This is not believed to be a problem with the logistic model, since the number of 0's and 1's are correctly predicted, but rather a problem with the logarithmic model. This is evident when one looks at the ROC values and the R^2 values for the growth classes. The ROC values are consistent with the other models developed. However the R^2 values appear lower than the other R^2 values for the present at time 1 (- 1) case. It appears that the model form chosen, has difficulty representing the curve form of the observed data. The significance of this depends on the purpose. Clearly in the REGEN II with trees case, the model over estimates in the 4 to 7 classes, then underestimates in the last class. Referring back to the classification scheme used in the wildlife classes, the 5 – 10 range represents two classes (6 and 7). For application, the predictions are not far from what is needed. For other applications, this may or may not be acceptable.

The statistical review of the models and an evaluation of the model performance is an important aspect of model acceptance, however the behaviour of the models is as or more important. To examine model behaviour the variables that make up the models must be examined and evaluated in terms of their respective coefficients.

5.2 Interpretation of coefficients

A model must be biologically plausible. Reviewing the variables that make up the model and their respective sign (+ or -), an evaluation of a models behaviour under different conditions can be made. This behaviour should be consistent with the known behaviour. Interestingly, both the logistic models and logarithmic models behave similarly, such that, when the same explanatory variables are present in both models, they possess the same behaviour represented by their respective sign of their coefficient (+ or -). This is intuitively correct since any explanatory variable which favours presence, should also favour quantity. It is also expected that the logistic and logarithmic models would be very similar in which explanatory variables make up the models. Reviewing both the logistic and logarithmic models, this study found that when comparing the paired logistic and logarithmic models, an average of 7 variables are common to both models. There is an average of 1 additional variable unique to the logistic models and an average of 5 additional variables unique to the logarithmic models. This clearly shows that this study was less interested in fitting parsimonious logarithmic models.

Although the interpretation of the coefficients may appear repetitive, it is quite the opposite. Firstly, the condition of the response variable at time 1, present or not present, differentiates between disappearing from a site versus encroaching onto a site. The factors that are important in these two instances can be quite different. Secondly, in the growth classes, the models are stratified into with trees and without trees. The processes which dictate the growth of REGEN I and REGEN II under a forest canopy versus no canopy, as discussed earlier are quite different. Finally, for the browse classes, each class has been developed within the inventory because of its unique properties. For these reasons, a brief review of the coefficients role in each of the models and perhaps their significance, when possible, is necessary. This review will be very useful to future users who, should then have a better understanding of the basis for the models.

The interpretations that were made during the discussion of the models come from many sources, books, journals, discussions with people and from plotting the response and explanatory variables spatially in ArcView. The interaction between the growth zones, soil types and vegetation types is well known. Through the plotting of the variables in ArcView, it was found that the modelling process chose the variables that best represented the influence, but what that influence is, for certain, is difficult to determine. For example, in the BLUEBERRY – 1 case, if one compares the distribution of blueberry to the variables in the model, the growth zones, soil groups and vegetation types where blueberry does not exist, usually have negative coefficients suggesting that they will tend to disappear. In areas were blueberry is commonly found, the coefficients are positive, as expected. Simple checks like these give much more merit to the model behaviour.

Some of the important variables, such as the response variable at time 1, the NO BROWSE variable and the change in basal area (*C_BA*) have already been discussed. The remaining variables with the exception of interval value are best discussed on a model by model basis. The interval value variable (*INTVAL*), tests whether or not there is a significant difference between an interval period of 5 or 6, dictated by the two inventory remeasurement intervals. Interval value appeared in 40 out of the 49 models, all wildlife browse models except Fern - 0 (logistic and logarithmic) and in only two of the logistic growth class models, REGEN I -1 no trees and in REGEN II - 0 no trees and only one logarithmic model, REGEN II – 1 with trees. When the response variable is "present at time 1", then *INTVAL* is always negative and always positive when "not present at time 1". This is as expected since interval values determines if a 1 year difference in measurement has an influence on change in status of the response variable. When we are predicting whether it will "stay" on a site, the longer the interval period, the more likely that change could occur, therefore it is negative. Similarly, if the response variable is not on the site at time 1, the longer the interval period, the more likely change could occur, therefore it is positive.

The following text discusses the significance and behaviour of the explanatory variables that are included in each of the models.

5.2.1 Logistic Models

5.2.1.1 Growth Classes

REGEN I - 1 (with trees)

If REGEN I *is present at time 1, what is the probability that* REGEN I *will be present at time 2, when an overstory exists.*

The positive coefficient for logarithm *A_NOSH_T1* suggests that when there are large areas with NO BROWSE, that the age of the stand is very young and will not likely grow into REGEN II in a 5 year period. The positive coefficient for the grass browse class (*A_GRSH_T1*) shows that as the density of grass increases, the probability of REGEN I staying REGEN I increases. This is intuitively correct since grass is expected to compete with the regeneration. In growth zones 7 (*GZD7*) and 10 (*GZD10*) the positive coefficients are interpreted to reflect the management practice of planting conifer species in primarily deciduous (beech) forested areas. The high deciduous competition suppresses the growth of conifers. In growth zone 19 and 20 (*GZD19* and *GZD20*) the negative coefficients suggest that it is less likely for REGEN I to stay REGEN I compared to other growth zones. The positive coefficient for the vegetation moist herb type (*GVD2*) suggests that competition may be higher than in other vegetation types. If it is a one layer stand (*SSD1_T2*) the negative coefficient shows that it is less likely to stay REGEN I. The positive coefficient for west aspect (*ASP7*) suggests that west exposures have slower growth rates. The negative coefficient for the POLE (*STANGSH_T2*) suggests that there are cases where REGEN I will grow from REGEN I into a POLE stand. The change in quadratic mean diameter (*C_QMD*) coefficient has a positive coefficient. This suggests that if there is harvesting from above, the probability of REGEN I staying is lower when compared to a stand where there is good growth.

REGEN I – 1 (no trees)

If REGEN I *is present at time 1, what is the probability that* REGEN I *will be present at time 2, when there are no overstory trees.*

The positive coefficient for *ELEV* shows that as elevation increases, the probability for REGEN I to stay REGEN I increases due to a slower growth rate. The positive coefficient for logarithm *A_NOSH_T1* suggests that when there are large areas with NO BROWSE, that the age of the stand is very young or very dense and will not likely grow into REGEN II in a 5 year period. The negative coefficient of *STD1_T2* shows that a spruce stand will be less likely to be present at time 2, compared to other species. This is correct since spruce has one of the highest juvenile growth rates. The negative coefficient for *RLD3, RLD4* and *RLD7* shows that in areas where water and nutrients pool (concave lower slopes, ditches and hollows), growth will be highest. The positive coefficient growth zones 9(*GZD9*), 10(*GZD10*) and 12(*GZD12*) is interpreted to reflect the management practice of planting conifer species in primarily deciduous (beech) forested areas. The high deciduous competition suppresses the growth of conifers.

REGEN II – 1 (with trees)

If REGEN II *is present at time 1, what is the probability that* REGEN II *will be present at time 2, when an overstory exists.*

The positive coefficient of *ELEV* indicates that as elevation increases, it is more likely that REGEN II will stay REGEN II. This is as expected, since growth will be slower as elevation increases. The negative coefficient of *STD1_T2* shows that spruce regeneration grows faster than other species. The logarithm *JUNGIISH_T1, SSD1_T1* and an interaction term between *SSD1_T1* and logarithm *JUNGIISH_T1* are interpreted together. In general, as *JUNGIISH_T1* increases the probability of REGEN II being present at time 2 increases. This shows the competition effect as density increases. If it is a single layer stand, the probability to stay REGEN II decreases since there is no definite stand of competing overstory trees. The interaction term shows that at low densities the difference between multilayer stands and single layer stands is much greater than when densities are high. The variable *A_NDSH_T1* in simple terms, represents conifer REGEN I. It has a positive coefficient which suggests that the more REGEN I present, the greater the chance that REGEN II will still be present at time 2. The negative coefficient for the change in quadratic mean diameter (*C_QMD*) can describe three general cases. When the *C_QMD* is positive, this suggests the stand has been thinned from below. When the *C_QMD* is negative, it suggest the stand has been harvested from above. When *C_QMD* is near zero, it represents normal growth. Thinning from below, when compared to a harvest, will result in the lowest probability for REGEN II being present at time 2 since, the REGEN II was what was removed during the low thinning.

REGEN II – 1 (no trees)

If REGEN II *is present at time 1, what is the probability that* REGEN II *will be present at time 2, when there are no overstory trees.*

The positive coefficient of *JUNGIISH_T1* shows that as the percent share of REGEN II at time 1 increases, the probability of REGEN II being present at time 2 increases. The positive coefficient of *ELEV* shows that as elevation increases, probability to stay increases. The negative coefficient for *SSD1_T2* shows that a one layer stand will be less likely to remain REGEN II when compared to a two layer or multilayer stand. In the inventory, by convention, a stand can be REGEN I or REGEN II but not both. THE CONIFEROUS BROWSE (*A_NDSH_T1*) and DECIDUOUS BROWSE

(*A_LASH_T1*) for the most part represent REGEN I. The coefficients for both of these are positive, suggesting that as the percentage of REGEN I increases, the younger the REGEN II stand is. The younger it is, the less likely it is that it can grow out of REGEN II into a POLE stand.

REGEN II – 0 (with trees)

If REGEN II *is not present at time 1, what is the probability that* REGEN II *will be present at time 2, when there are overstory trees.*

The positive coefficient of *JUNGISH_T1* shows that as the percent share of REGEN I increases, there is higher chance that REGEN II will be present at time 2. The negative coefficient of *ELEV* shows that as elevation increases, probability for REGEN II to encroach onto a site decreases. The negative coefficient of *SSD1_T2* shows that multilayer stands have a better chance of having REGEN II appear than a 1 layer stand. The coefficients for dystric cambisols (*SCD3*) and spodi-dystric cambisols (*SCD4*) are both positive. These two soil types are very common and are found throughout Austria. In relation to other soil types, it is expected that growth will be better on these soils, therefore the chance of encroachment of REGEN II should be higher. The negative coefficients for growth zones 7(*GZD7*), 9(*GZD9*) and 10(*GZD10*) are interpreted to reflect the management practice of planting conifer species in primarily deciduous (beech) forested areas. The high deciduous competition suppresses the growth of conifers therefore they are unlikely to encroach onto a site. The negative coefficient of *A_NOSH_T1* suggests that when there are large areas with NO BROWSE, the understory vegetation is either very young or low to the ground and/or the density of the canopy above is very high, suppressing the growth of ground vegetation. The positive coefficient for the *STD0_T2* variable suggests that if there are no trees in the angle count at time 2. Therefore the canopy is not dense providing more light to the forest floor. The positive lower slope relief (*RLD3*) coefficient shows that encroachment is highest where growth is best, for example where water and nutrients pool.

REGEN II – 0 (no trees)

If REGEN II *is not present at time 1, what is the probability that* REGEN II *will be present at time 2, when there is an overstory.*

The negative coefficient of *ELEV* shows that as elevation increases, the probability for REGEN II to encroach onto a site decreases. The positive coefficient of *JUNGISH_T1* shows that as the percent share of REGEN I at time 1 increases, there is a higher chance that REGEN II will be present at time 2. The negative coefficient of NO BROWSE (*A_NOSH_T1*) suggests that when there are large areas with "NO BROWSE", the understory vegetation is either very young or low to the ground and/or the density of the canopy above is very high, suppressing the growth of ground vegetation. The positive coefficients for the lower slope relief (*RLD3*) and hollows (*RLD7*) shows that encroachment is highest where growth is best, for example where water and nutrients pool. The negative coefficient in growth zones 6(*GZD6*), 9(*GZD9*), 10(*GZD10*) and 12(*GZD12*) may reflect the management practice of planting conifer species in primarily deciduous (beech) forested areas.

5.2.1.2 Wildlife browse Classes

NO BROWSE - 1

If there are areas with NO BROWSE *present at time 1, what is the probability that there will be areas with* NO BROWSE *present at time 2.*

The positive coefficient of *A_NOSH_T1* indicates that with an increasing percent share of NO BROWSE (areas completely void of browsable vegetation) at time 1, the probability of having NO BROWSE at time 2 increases. The positive coefficients for REGEN II (*JUNGIISH_T1*) and POLE (*STANGSH_T2*) show that as the density of either of these two layers increases, the probability of NO BROWSE increases. The *STD0_T2* and *CCF_T2* represent the stand density at time 2. The negative coefficient of *STD0_T2* indicates that if there are no trees in the angle count, the stand is not dense, allowing sufficient light to reach the forest floor for vegetation to encroach. The positive coefficient for *CCF_T2* suggests that as the *CCF_T2* increases, the probability for NO BROWSE increases. Both 1 layer stands (*SSD1_T2*) and mixed deciduous stands (*STD41_T2*) have negative coefficients indicating that in these cases, the probability of NO BROWSE is lower. The sparse moss type (*GVD6*) has a positive coefficient. This type is a large vegetation group represented mostly in coniferous regions. It is expected that coniferous regions would have less browse than when compared to deciduous types. The change in basal area (*C_BA*) variable has a positive coefficient suggesting that if a stand is harvested the probability for NO BROWSE should be lower, since opening up of the canopy allows for more understory vegetation.

NO BROWSE - 0

If there are no areas with NO BROWSE *present at time 1 (100% coverage by browsable vegetation), what is the probability that there will be areas with* NO BROWSE *present at time 2.*

NO BROWSE when NO BROWSE is not present at time 1, indicates that all the area available for understory vegetation is fully occupied. The elevation (*ELEV*) coefficient is negative indicating that as elevation increases, the probability of NO BROWSE occurring, when one does not exist at time 1, is lower. This is as expected since growth is slower at higher elevations, so change will occur much slower. The shade tolerant herb (*GVD1*), the moist herb (*GVD2*), the moderhumus in conifer stand (*GVD4*) and the sparse moss (*GVD6*) types all have positive coefficients indicating that in these vegetation types, more NO BROWSE will be present at time 2 compared to other vegetation types. The square of *OVERSH_T2* is a summation of the percent shares of, POLE (*STANGSH_T2*), MATURE I(*BHISH_T2)* and MATURE II(*BHIISH_T2*) squared. These variables along with REGEN I (*JUNGIISH_T1*) have positive coefficients showing that if an area is fully occupied, the probability of having NO BROWSE at time 2, will increase with the increase in the shares of these variables. In growth zone 15 (*GZD15*) and 18 (*GZD18*) the positive coefficients indicate that for some reason in these regions, areas of NO BROWSE will appear more often than in other regions. In growth zone 9 (*GZD9*) the opposite is true. The negative coefficient of *STD0_T2* indicates that if there are no trees in the angle count, the stand is not dense, allowing sufficient light to reach the forest floor for vegetation to encroach. Thus the probability for areas WITH NO BROWSE to appear is lower. The positive coefficient for *STD1_T2* indicates that if the stand type is pure spruce, the probability for areas of NO BROWSE to appear is higher, since spruce will quickly grow out of the browsable region. This is the same for the square of *ASUNGSH_T1* representing the sum of the CONIFER (*A_NDSH_T1*), DECIDUOUS (*A_LASH_T1*) and SHRUB (*A_STSH_T1*) BROWSE, squared. These 3 types are tree and shrub types which will either grow out of the browsable region or become dense enough to prevent other browsable species to appear below, therefore the probability for

NO BROWSE will increase. The variable GRASS BROWSE (*A_GRSH_T1*) has a negative coefficient which indicates that as the percent share of grass increases at time 1, the probability of an area with NO BROWSE forming is lower. This is intuitively correct since grass will not grow out of the browsable region and is a good competitor when compared to other browse species. The change in basal area (*C_BA*) coefficient is positive suggesting that when the area is harvested there will be less NO BROWSE being present at time 2. The positive coefficient for the eutric cambisol soil group (*SCD3*) suggests that in this soil group the probability for NO BROWSE to appear is higher.

CONIFER BROWSE - 1

If CONIFER BROWSE *is present at time 1, what is the probability of* CONIFER BROWSE *being present at time 2 .*

The coefficients for variables pure Norway spruce (*STD1_T2*), one layer stands (*SSD1_T2*) are negative. The negative coefficients indicate that in these cases the probability of CONIFER BROWSE being present at time 2 is lower. This is as expected since in these cases conifer growth would be expected to be very good. Norway spruce has a high juvenile conifer growth rate and one layer stands have no overtopping vegetation to suppress growth. The shade herb vegetation type (*GVD1*) also has a negative coefficient, however this type is predominantly in growth zones 9 and 10 which are deciduous areas. In this case the CONIFER BROWSE may be decreasing due to high competition from deciduous species like beech. The NO BROWSE (*A_NOSH_T1*) variable has a negative coefficient suggesting that as the area of NO BROWSE increases the probability of CONIFER BROWSE decreases. This is also represented by the negative coefficients for variables REGEN II (*JUNGIISH_T1*) and POLE (*STANGSH_T2*), which indicate that in these cases the stand is either exiting the browsable region and/or suppressing growth below. The soil group variables, spodi-dystric cambisols (*SCD4*), substrate induced podzols (*SCD6*), the leptosols *(SCD17 and SCD18)* have positive coefficients suggesting that in these soil types growth is poorer. In growth zones, 12 (*GZD12*), 17 *(GZD17)* and 18 (*GZD18*) the probability of CONIFER BROWSE is higher. The change in basal area (*C_BA*) coefficient is negative suggesting that after harvesting there is a higher probability of CONIFER BROWSE being present at time 2, compared to a non harvest scenario.

CONIFER BROWSE – 0

If CONIFER BROWSE *is not present at time 1, what is the probability of* CONIFER BROWSE *being present at time 2.*

Elevation (*ELEV*) and elevation squared ($ELEV^2$) have positive and negative coefficients respectively. This indicates that, as elevation increases there is a higher probability that conifer will encroach onto a site, to a maximum, which exists at approximately 1300 meters in elevation. The *STD0_T2* variable specifies if there are no trees in the angle count at time 2. The coefficient is positive which suggests that when there are no trees in the angle count, the density of the canopy is lower, therefore there is a higher probability of conifer encroachment onto a site. The *SSD1_T2* and *SSD2_T2* variables have negative coefficients indicating that if a stand is one layered or 2 layered, it is less likely to have conifer encroach compared to a 3 layer stand. In growth regions 18 (*GZD18*) and 20 (*GZD20*) the probability for conifer to encroach onto a site is higher compared to all other regions. The shade tolerant herb type (*GVD1*) has a negative coefficient which supports the theory posed in Conifer –1, that competition is high with deciduous species. The sparse moss type (*GVD6*) has a positive coefficient showing the increasing probability for encroachment in this primarily conifer vegetation type.

DECIDUOUS BROWSE - 1

If DECIDUOUS BROWSE *is present at time 1, what is the probability of* DECIDUOUS BROWSE *being present at time 2.*

If the percent share of DECIDUOUS BROWSE present at time 1 increases, represented by the logarithm *A_LASH_T1*, the positive coefficient shows that the probability of DECIDUOUS BROWSE being present at time 2 also increases. The *ELEV* coefficient is negative indicating that as elevation increases, the probability of DECIDUOUS BROWSE staying on the site is lower. This is also supported by the upper slope relief variable (*RLD1*) which also has a positive coefficient. The positive coefficients for growth zone 9 (*GZD9*) and 10 (*GZD10*) identifies the primarily deciduous growth zones. The coefficient for the eutric planosol soil group 11 (*SCD11*) is positive and is found in the flysch zone of Austria and overlaps growth zones 7 and 8. These soils are heavy in nutrients, supporting primarily deciduous species. Conversely, the moderhumus vegetation type (*GVD4*) which primarily supports coniferous species, has a negative coefficient.

This is also supported by the pure Norway spruce type (*STD1_T2*) which has a negative coefficient. The NO BROWSE (*A_NOSH_T1*) variable has a negative coefficient suggesting that as the area of NO BROWSE increases the probability of DECIDUOUS BROWSE decreases. The change in basal area (*C_BA*) coefficient is negative which shows that after harvesting, the probability OF DECIDUOUS BROWSE being present at time 2 is higher, compared to a non harvest scenario.

DECIDUOUS BROWSE – 0

If DECIDUOUS BROWSE *is not present at time 1, what is the probability of* DECIDUOUS BROWSE *being present at time 2.*

Elevation (*ELEV*) and elevation squared (*ELEV*^{2}) have positive and negative coefficients respectively. This indicates that as elevation increases there is a higher probability that deciduous will encroach onto a site, to a maximum, which exists at approximately 500 meters in elevation. The logarithm NO BROWSE (*A_NOSH_T1*) has a negative coefficient suggesting that as the area of NO BROWSE increases the probability of DECIDUOUS BROWSE encroaching decreases. The negative coefficient of the pure Norway spruce type (*STD1_T2*) shows that the probability of deciduous species encroaching in this type is lower. Conversely, if the stand type is pure beech or mixed deciduous the probability is higher, illustrated by the positive coefficients for *STD10_T2* and *STD41_T2*. In the shade tolerant herb type (*GVD1*), the moderately moist herb type (*GVD2*), thermophilic herb types (*GVD3*) and the hydrophytic perennial shrub type (*GVD19*) the coefficients are all positive. All these vegetation types support deciduous species. Unexpectedly, the moderhumus type (*GVD4*) is also positive. In growth zones 1 (*GZD1*) and 4 (*GZD4*) the probability of deciduous encroaching onto a site is lower, illustrated by the negative coefficient. This is probably due to the acidic soils in these regions. In the primarily deciduous growth zones (*GZD8*) and (*GZD10*) the coefficients are positive. The change in basal area (*C_BA*) coefficient is negative which suggests that after harvesting the probability of DECIDUOUS BROWSE being present at time 2 is higher, compared to a non harvest scenario.

SHRUB BROWSE – 1

If SHRUB BROWSE *is present at time 1, what is the probability of* SHRUB BROWSE *being present at time 2 .*

As the percent share of SHRUB BROWSE present at time 1 increases, represented by the variable *A_STSH_T1*, the positive coefficient shows that the probability of SHRUB BROWSE being present at time 2 also increases. The *ELEV* coefficient is negative indicating that as elevation increases, the probability of the specified shrubs staying on the site decreases. The positive slope coefficient (*SLPE*) shows that as the slope increases the probability of shrubs staying increases. THE NO BROWSE (*A_NOSH_T1*) variable has a negative coefficient suggesting that as the area OF NO BROWSE increases the probability of SHRUB BROWSE decreases. This is also the case with the variable REGEN II (*JUNGIISH_T1*) which has a negative coefficient. The spodi-dystric cambisols (*SCD4*) has a negative coefficient which supports that the shrub species prefer less acidic soil types. This is also the case with the negative coefficient for the moderhumus in conifer type (*GVD4*) which is more acidic. The hydrophytic perennial shrub type (*GVD19*) represents very wet sites and although the species listed prefer moist sites these sites may be too wet. In growth zone 20 (*GZD20*) the negative coefficient suggests that SHRUB BROWSE will disappear between time 1 and time 2.

SHRUB BROWSE – 0

If SHRUB BROWSE *in not present at time 1, what is the probability of* SHRUB BROWSE *being present at time 2.*

The *ELEV* coefficient is negative which indicates that as elevation increases, the probability of the specified shrubs encroaching onto the site decreases. However elevation interacts with both the growth zone 13 (*GZD13*) and the group of growth zones (*GRP_GZ*; 11(*GZD11*), 12(*GZD12*), 15(*GZD15*), 17(*GZD17*) and 18 (*GZD18*)). The interaction of elevation with growth zone 13 indicates that when in this growth zone, the slope of the relationship is different. In this case probability of SHRUB BROWSE to appear is much higher at lower elevations and only moderately higher at higher elevations. The interaction with the group of growth zones is similar to growth zone 13, such that it is higher than all other growth zones, but the slope remains much higher over all elevations. The negative coefficient for 1 layer stands (*SSD1_T2*) shows that in these cases, the encroachment of shrubs is less likely when compared to 2 or multilayer stands. Similarly, the negative coefficient for the pure beech stand type (*STD10_T2*) indicates that beech is a much better competitor not allowing for encroachment by the shrub species. The positive coefficient for the shade tolerant herb type (*GVD1*), the subapline dwarf shrub type (*GVD14*) and the hydrophytic perennial shrub type (*GVD19*) shows that these vegetation types support the shrubs listed. Inversely, the moss types (*GVD6* and *GVD7*) do not support these species. The positive coefficients for the southeast aspect (*ASD4*) and the southwest aspect (*ASD6*) shows that the species of shrubs listed prefer sunny drier locations. The NO BROWSE (*A_NOSH_T1*) variable has a negative coefficient suggesting that as the area of NO BROWSE increases the probability of SHRUB BROWSE encroaching decreases. The change in basal area (*C_BA*) coefficient is negative which shows that after harvesting the probability of SHRUB BROWSE being present at time 2 is higher, compared to a non harvest scenario.

RASPBERRY BROWSE – 1

If RASPBERRY BROWSE *is present at time 1, what is the probability of* RASPBERRY BROWSE *being present at time 2.*

As the percent share of RASPBERRY BROWSE present at time 1 increases, represented by the variable *A_HISH_T1*, the positive coefficient shows that the probability of RASPBERRY BROWSE being present at time 2 also increases. The *ELEV* coefficient is negative indicating that as elevation increases, the probability of RASPBERRY BROWSE staying on the site decreases. The *A_NOSH_T1* variable has a negative coefficient suggesting that as the area of NO BROWSE increases the probability of RASPBERRY BROWSE decreases. This is also the case with the REGEN II variable *JUNGIISH_T1* which also has a negative coefficient. The negative coefficient for the pure Norway spruce stand type (*STD1_T2*) indicates that raspberry is less likely to continue to be present under a spruce stand compared to other stand types. The coefficients for the leptosols (*SCD17*) and fluvisols (*SCD22*) are negative. Leptosols are weakly developed soils, low in nutrients which is unfavourable for raspberry. Fluvisols are also occasionally flooded. Although Ellenberg (1996) suggests that raspberry is indifferent to water supply, it would make sense to believe that any plant that prefers open sunlight, is more apt to accept moderate moisture conditions. Being flooded occasionally, would be excessive. This could explain the negative coefficient. The coefficients for the moderhumus vegetation type (*GVD4*) and the hydrophytic perennial shrub type (*GVD19*) are positive showing raspberries preference for the conditions in these vegetation types.

RASPBERRY BROWSE– 0

If RASPBERRY BROWSE *is not present at time 1, what is the probability of* RASPBERRY BROWSE *being present at time 2.*

The *ELEV* coefficient is negative indicating that as elevation increases, the probability of RASPBERRY BROWSE encroaching onto the site decreases. The *STD0_T2* variable indicates that the subplot has no trees in the angle count at time 2. The positive coefficient shows that if the overstory of a stand is not very dense, raspberry is more likely to encroach onto the site. The coefficients for the moderhumus vegetation type (*GVD4*), the hydrophytic perennial shrub type (*GVD19*) and the shade tolerate herb type (*GVD1*), are positive showing raspberries preference for the conditions in these vegetation types. The negative coefficient for growth zone 17 (*GZD17*) indicates that it is less likely for raspberry to encroach onto a site when it is in this zone. The logarithm NO BROWSE (*A_NOSH_T1*) variable has a negative coefficient suggesting that as the area of NO BROWSE increases the probability of RASPBERRY BROWSE encroaching decreases. The coefficients for the leptosols (*SCD17* and *SCD18*), the chromic cambisols (*SCD19*), the gleysols (*SCD20*) and the fluvisols (*SCD21*) are all negative. This shows raspberries preference for drier more nutrient rich sites. The change in basal area (*C_BA*) coefficient is negative and the square of change in basal area is positive suggesting that when a stand is harvested there is a higher probability of RASPBERRY BROWSE being present at time 2, compared to a non harvest scenario.

BLUEBERRY BROWSE - 1

If BLUEBERRY BROWSE *is present at time 1 what is the probability of* BLUEBERRY BROWSE *being present at time 2.*

The BLUEBERRY BROWSE variable (*A_HESH_T1*) has a positive coefficient which suggests that as the percent share of blueberry at time 1 increases, the probability of blueberry being present at time 2 increases. Elevation (*ELEV*) has a positive coefficient which is intuitively correct since we expect blueberry to favour higher altitudes. The slope coefficient (*SLPE*) is negative suggesting that as slope increases, the probability of blueberry staying on the site decreases. The *STD0_T2* variable indicates if a subplot has no trees in the angle count at time 2. The negative coefficient shows that if the overstory of a stand is not very dense, blueberry will disappear from the site, which is intuitively correct since blueberry prefers shade (Ellenberg 1996). In growth region 17 (*GZD17*) the probability of blueberry staying blueberry is less than all other growth regions. If the soil group is dystric cambisols (*SCD2*), the probability of blueberry being present at time 2 decreases in comparison to other soil types. The reason for this is not intuitively clear, since soil group 2 is an acidic type which favours blueberry. It is possible that where this soil type occurs, the elevation is much lower or the soil type is too acidic. The sparse moss ground vegetation type (*GVD6*) is a blueberry type therefore it is expected that the probability increases if it is in this type. Conversely, it is not surprising that the coefficients for the moderhumus type (*GVD4*) and the hydrophytic perennial herb type (*GVD19*) are negative. The moderhumus type is not as acidic as blueberry would prefer and the hydrophytic type is much wetter. The change in basal area (*C_BA*) coefficient is negative which suggests that after harvesting there is a lower probability of BLUEBERRY BROWSE being present at time 2, compared to a non harvest scenario.

Blueberry - 0

If BLUEBERRY BROWSE *is not present at time 1, what is the probability of* BLUEBERRY BROWSE *being present at time 2.*

Elevation (*ELEV*) has a positive coefficient which is intuitively correct since we expect blueberry to favour higher altitudes. The slope coefficient (*SLPE*) is negative suggesting that as slope increases, the probability of blueberry encroaching on the site decreases. The sparse moss ground vegetation type (*GVD6*) is a blueberry type, therefore, it is expected that the probability increases in this type. The positive coefficients for the northeast aspect (*ASD2*) and the northwest aspect (*ASD8*) shows that blueberry prefers shaded locations. The positive coefficients for the dystric cambisols (*SCD2*), the spodi-dystric cambisols (*SCD4*) and the podzols (*SCD5* and *SCD6*) suggests that blueberry is more likely to encroach on these soil types compared to the other types. The negative coefficient for the mixed deciduous stand type (*STD41_T2*) indicates that the probability of blueberry encroaching onto a site when it is mixed deciduous is lower. The percent share of REGEN I at time 1, squared, (*JUNGISH_T1*) has a negative coefficient. This shows that as the percent share of REGEN I increases, the probability of blueberry encroaching onto a site decreases. This shows that blueberry is in direct competition with REGEN I and is not the better competitor. The crown competition factor at time 2 (*CCF_T2*) has a negative coefficient. This suggests that although blueberry prefers shaded areas, it becomes more difficult to encroach onto a site as the overstory density increases.

ERICA - 1

If ERICA BROWSE *is present at time 1 what is the probability of* ERICA BROWSE *being present at time 2.*

The negative coefficient for water regime (*WTRG*) shows that as the site becomes wetter the probability of ERICA staying on a site decreases. The coefficient for the variable representing growth zone 1 (*GZD1*) is negative showing that the probability of ERICA staying in this zone is much less than other zones. The ERICA ground vegetation type (*GVD15*) is an "Erica" type therefore it is expected that the probability of ERICA staying on the site increases if it is in this type.

ERICA – 0

If ERICA BROWSE *is not present at time 1 what is the probability of* ERICA BROWSE *being present at time 2.*

The negative coefficient for water regime (*WTRG*) shows that as the site becomes wetter the probability of ERICA encroaching onto a site decreases. The ERICA ground vegetation type (*GVD15*) is an "*Erica*" type therefore it is expected that the probability of ERICA encroaching onto this site increases in this type. Interestingly, the positive coefficients for the moss ground vegetation type (*GVD5* and *GVD6*), the blueberry type (*GVD9*) and the pasture forest type (*GVD16*) shows that the probability for ERICA to encroach onto these sites is higher than other vegetation types. The positive coefficients for the leptosols (*SCD17* and *SCD18*) suggest that ERICA is more likely to encroach onto these soil types compared to other types. The *A_NOSH_T1* variable has a negative coefficient suggesting that as the area of NO BROWSE increases the probability of ERICA encroaching decreases.

HERBS - 1

If HERB BROWSE *is present at time 1 what is the probability of* HERB BROWSE *being present at time 2.*

The variable logarithm *A_KRSH_T1* has a positive coefficient which suggests that as the percent share of HERB BROWSE at time 1 increases, the probability of HERB BROWSE being present at time 2 increases. The negative coefficient for the pure Norway spruce type (*STD1_T2*) shows that the probability of HERB BROWSE staying under a spruce canopy is lower. This is also the case for the spodi-dystric cambisol soil group (*SCD4*) which has a negative coefficient. The negative coefficients for the moss ground vegetation types (*GVD5* and *GVD6*), the *Avenella* type (*GVD8*) and the *Erica* type (*GVD15*) show that HERB BROWSE, if present in these types at time 1, have a lower probability of staying compared to other types. In growth zones 1 and 4 (*GZD1* and *GZD4*) the coefficients are also negative. In all the cases above where the probability of herbs staying decreases, the reason is most likely the acidic soil. For growth zones 9, 10, 12 (*GZD9, GZD10 GZD12*) and 17 (*GZD17*) the coefficients are positive, showing that the probability of staying increases in these zones compared to other zones. The positive coefficient for the quadratic mean diameter at time 2 (*QMD_T2*) shows that as stands become older, the probability for HERB BROWSE to stay on the site increases. The negative coefficient for percent share of REGEN I (*JUNGISH_T1*) and REGEN II (*JUNGIISH_T1*) at time 1 shows that as the density of these two growth classes increases, the probability of HERB BROWSE staying on the site decreases.

HERBS - 0

If HERB BROWSE *is not present at time 1 what is the probability of* HERB BROWSE *being present at time 2.*

In growth zone 1 (*GZD1*) the coefficient is negative suggesting that the probability for HERB BROWSE to encroach onto a site in this zone is lower than other zones. The reason is most likely the acidic soil of this zone. The coefficients for the shade tolerant herb type (*GVD1*), the moderately moist herb type (*GVD2*) and the hydrophytic perennial shrub type (*GVD19*) are positive. These are herb types, therefore it is expected that the probability for HERB BROWSE to encroach on these sites is higher than other types. Conversely, the two moss types (*GVD5* and *GVD6*) have negative coefficients showing the dislike of these types by herbs. The *A_NOSH_T1* variable has a negative coefficient suggesting that as the area of NO BROWSE increases the probability of HERB BROWSE encroaching decreases. The coefficients for the stagnic gleysols (*SCD14*), the leptosols (*SCD17* and *SCD18*) and the chromic cambisols (*SCD19*) are all positive. This shows the herb's ability to encroach onto rendzic soil types or soils with hydromorphic characteristics. The change in basal area squared (*C_BA*) coefficient is positive suggesting that after harvesting there is a lower probability of HERB BROWSE encroaching at time 2, compared to a non harvest scenario. The positive coefficient for the quadratic mean diameter at time 2 (*QMD_T2*) shows that as stands become older, the probability for HERB BROWSE to encroach into them increases. The positive coefficient for the lower slope relief variable (*RLD3*) shows that where nutrients and moisture pools, there is a higher probability for HERB BROWSE to encroach compared to other positions of relief.

FERNS - 1

If FERN BROWSE *is present at time 1 what is the probability of* FERN BROWSE *being present at time 2.*

The variable logarithm *A_FASH_T1* has a positive coefficient which suggests that as the percent share of ferns at time 1 increases, the probability of ferns being present at time 2 increases. The positive coefficient for water regime (*WTRG*) shows that as the site becomes wetter the probability of ferns staying on a site increases. The square root of elevation (*ELEV*) has a positive coefficient which suggests that ferns favour higher altitudes. The negative coefficient for the southeast (*ASD4*), south (*ASD5*) and the southwest (*ASD6*) facing slopes shows ferns dislike for the hotter, drier aspects. From the positive coefficient of the moderhumus ground vegetation type (*GVD4*), it can be seen that ferns prefer this vegetation type. Conversely, the more competitive, grass cover type (*GVD12*) has a negative coefficient showing the ferns inability to compete with grasses. For growth zones 1 (*GZD1*), 4 (*GZD4*), 8 (*GZD8*) and 12 (*GZD12*) the coefficients are positive showing that if ferns are present at time 1 in these zone, the probability for them to stay at time 2 is higher compared to other zones. Conversely, for growth zone 17 (*GVD17*) the probability for ferns to stay at time 2 is lower.

FERNS - 0

If FERN BROWSE *is not present at time 1 what is the probability of* FERN BROWSE *being present at time 2.*

The positive coefficient for water regime (*WTRG*) shows that as the site becomes wetter the probability of ferns encroaching onto a site increases. The positive coefficient for the pure Norway spruce type (*STD1_T2*) indicates that ferns prefer this type over other types. The positive coefficient for the north (*ASD1*), northeast (*ASD2*) and the northwest (*ASD8*) facing slopes shows ferns preference for shady aspects. The positive coefficient for the quadratic mean diameter at time 2 (*QMD_T2*) shows that as stands become older, the probability for ferns to encroach increases. From the positive coefficient of the moderhumus ground vegetation type (*GVD4*) and the hydrophytic perennial shrub type (*GVD19*), it can be seen that ferns will encroach onto these sites more than other types. The coefficients for the stagnic gleysols (*SCD14*) and the spodi-dystric cambisols (*SCD4*) are positive indicating that ferns are more likely to encroach onto sites with these soils than others. The coefficients for growth zone 8 (*GZD8*), 11 (*GZD11*) and 12 (*GZD12*) are all positive. This indicates that in these growth zones, ferns are more likely to encroach. Conversely, in growth zones 18 (*GZD18*) and 20 (*GZD20*) the opposite is true.

GRASS - 1

If GRASS BROWSE *is present at time 1 what is the probability of* GRASS BROWSE *being present at time 2.*

The logarithm(*A_GRSH_T1*) has a positive coefficient which shows that as the percent share of grass at time 1 increases, the probability of grass being present at time 2 increases. Elevation (*ELEV*) has a positive coefficient which suggests that grass is a better competitor at higher elevations. The negative coefficients for REGEN I (*JUNGIISH_T1)* and POLE (*STANGSH_T2*) shows that as the density of these growth classes increases, the probability for grass to stay on the site decreases. The change in basal area (*C_BA*) coefficient is negative suggesting that after harvesting there is a higher probability of grass being present at time 2, compared to a non harvest scenario. The positive coefficient for the leptosol soil group (*SCD17*) shows grasses strength as a competitor on poor sites where there is less competition from above. The negative coefficient for the eutric cambisols (*SCD3*) shows that on very basic sites, grass is less of a competitor compared to other soil types. In the shade tolerant herb vegetation type (*GVD1*), the moderhumus in conifer stands (*GVD4*), the moss types (*GVD5* and *GVD6*), the hydrophytic perennial shrub type (*GVD19*) and the *Calluna* type (*GVD10*), the coefficients are negative suggesting that grass is less of a competitor in these types compared to other vegetation types. In growth zone 1 (*GZD1*) and 2 (*GZD2*) the coefficients are both positive indicating that grasses compete well in these zones. Conversely, in growth zone 11 (*GZD11*) grasses are not as competitive as shown by the negative coefficient.

GRASS – 0

If GRASS BROWSE *is not present at time 1 what is the probability of grass being present at time 2.*

Elevation (*ELEV*) has a positive coefficient which suggests that grass is a better competitor at higher elevations. The *STD0_T2* variable indicates that the subplot has no trees in the angle count at time 2. The positive coefficient shows that if the overstory of a stand is not very dense, grass is more likely to encroach onto the site. In pure beech stand types (*STD10_T2*) the negative coefficient shows that grass is less likely to encroach onto a site compared to other stand types. The *A_NOSH_T1* variable has a negative coefficient suggesting that as the area of NO BROWSE increases the probability of GRASS BROWSE encroaching decreases. The negative coefficients for REGEN I (*JUNGIISH_T1)* and POLE (*STANGSH_T2*) shows that as the density of these growth classes increases, the less grass will encroach onto a site. The change in basal area (*C_BA*) coefficient is negative suggesting that after harvesting there will be a higher probability of grass encroaching onto a site, compared to a non harvest scenario. In the *Avenella* (*GVD8*) and the competing grass (*GVD12*) ground vegetation types the coefficients are positive as expected. In the moderhumus type (*GVD4*) the coefficient is negative showing grasses less competitive nature in this vegetation type. In growth zone 1 (*GZD1*) the coefficient is positive showing that the probability of grass encroaching is higher compared to other growth zones. In growth zone 17 (*GZD17*) the opposite is true.

5.2.2 Logarithmic Regressions

5.2.3 Growth Classes

REGEN I - 1 (with trees)

If REGEN I *is present at time 1, in what quantity will it be present at time 2, when an overstory exists*

Unlike the logistic model, the state of REGEN I (*JUNGISHT_T1*) at time 1 was important in quantifying it. The coefficient is positive therefore as the percent share of REGEN I increases the quantity of REGEN I being present at time 2 increases. The positive coefficient for logarithm *A_NOSH_T1* suggests that when there are large areas with NO BROWSE, the age of the stand is very young and will only become taller and denser. The positive coefficient for the grass browse class (*A_GRSH_T1*) shows that as the density of grass increases, more REGEN I will be present at time 2. This is correct since the reduced growth due to competition will only increase the quantity of REGEN I not allowing it to grow out of the class. In growth zones 7 (*GZD7*), 9 (*GZD9*) and 10 (*GZD10*) the positive coefficients are interpreted to reflect the management practice of planting conifer species in primarily deciduous (beech) forested areas. The high deciduous competition suppresses the growth of conifers. As with grass competition, the quantity increases, but it does not grow out of the class. In growth zone 19 and 20 (*GZD19* and *GZD20*) the negative coefficients suggest that growth is better or there is less competition, therefore the Regen I will grow into Regen II. The positive coefficient for the vegetation moist herb type (*GVD2*) suggests that competition may be higher than in other vegetation types. If it is a two layer stand (*SSD2*) the positive coefficient shows that more REGEN I will be present at time 2. The positive coefficient for west aspect (asp7) suggests that west exposures have slower growth rates. The change in quadratic mean diameter (*C_QMD*) coefficient has a positive coefficient. This suggests that if there is harvesting from above, the more REGEN I be on the site due to the newly opened area.

REGEN II – 1 (with trees)

If REGEN II *is present at time 1, in what quantity will it be present at time 2, when an overstory exists*

The logarithm REGEN II (*JUNGIISH_T1*) status at time 1 shows that as the percent share of REGEN II at time 1 increases, the quantity at time 2 increases. The positive coefficient for *ELEV* indicates that as elevation increases, more REGEN II will be present at time 2. The negative coefficient of the pure Norway spruce stand (*STD1_T2*) shows that spruce grows faster than other species. If it is a single layer stand (*SSD1_T2*), there is less REGEN II at time 2, since there is no dense stand of competing overstory trees. In growth zones 6 (*GZD6*), 11 (*GZD11*) and 20 (*GZD20*) the positive coefficients suggest that the amount of REGEN II at time 2 will increase. The variable logarithm *A_NDSH_T1* represents conifer REGEN I. It has a positive coefficient which suggests that the more REGEN I present (young conifer), the more REGEN II will be present at time 2. In pure beech stand types (*STD10_T2*) the positive coefficient suggests that more beech will be present at time 2. The *C_BA* variable has a negative coefficient which suggest that after harvesting, more REGEN II will be present at time 2.

REGEN II – 1 (no trees)

If REGEN II *is present at time 1, in what quantity will it be present at time 2, when no overstory exists.*

The logarithm REGEN II (*JUNGIISH_T1*) status at time 1 shows that as the percent share of REGEN II at time 1 increases, the quantity at time 2 increases. Elevation (*ELEV*) and one layer stands (*SSD1_T2*) interact. The *SSD1_T2* has a negative coefficient and the interaction term (*ELEV* x *SSD1_T2*) has a positive coefficient. The combination of these variables shows that elevation only has an effect in one layer stands. In one layer stands, as the elevation increases, more REGEN II will be present at time 2. In the inventory, by convention, a stand can be REGEN I or REGEN II but not both. The logarithm *A_NDSH_T1* and logarithm *A_LASH_T1* represent conifer and deciduous REGEN I and to some degree REGEN II from time 1. The coefficient for both of these are positive, suggesting that as the percentage of REGEN I increases, the younger the REGEN II stand is. The younger it is, the higher the quantity of REGEN II at time 2, since it is unlikely to grow into a POLE stand. In growth zones 3 (*GZD3*), 7 (*GZD7*) and 19 (*GZD19*) the negative coefficients suggest that the amount of REGEN II at time 2 will decrease. If there are no trees in the angle count at time 2 (*STD0_T2*), the negative coefficient suggests that the amount of REGEN II at time 2 will decrease. The negative coefficients for the soil groups gleysols (*SCD20*) and fluvisols (*SCD22*) show that the wetter sites have better growth therefore less REGEN II will remain at time 2. The soil group ferralic cambisol (*SCD15*) also has a negative coefficient, however the underlying reason is unknown. In the moist herb (*GVD2*), the moderhumus in conifer stands (*GVD4*) and the moss type (*GVD7*) the coefficients are negative. This shows the good growth that occurs in these areas and indicates that at time 2 there is less REGEN II.

REGEN II – 0 (with trees)

If REGEN II *is not present at time 1, in what quantity will it be present at time 2, when an overstory exists.*

The positive coefficient of logarithm *JUNGISH_T1* shows that as the percent share of REGEN I increases, the higher quantity of REGEN II will be present at time 2. The negative coefficient of *ELEV* shows that as elevation increases, the less REGEN II will be found at time 2. The negative coefficient of *SSD1_T2* shows that one layer stands will have less REGEN II appearing than multilayer stands. The coefficients for soil types *SCD3* and *SCD4* are both positive. In relation to other soil types, it is expected that growth will be better. Therefore, more REGEN II should appear at time 2. The negative coefficient in *GZD7*, *GZD9* and *GZD10* is interpreted to reflect the management practice of planting conifer species in primarily deciduous (beech) forested areas. The high deciduous competition suppresses the quantity of conifers that encroach onto a site. The negative coefficient of *A_NOSH_T1* suggests that when there are large areas with NO BROWSE, the understory vegetation is either very young or low to the ground and/or the density of the canopy above is very high, suppressing the amount of REGEN II that encroaches. The positive coefficient for the *STD0_T2* variable suggests that if there are no trees in the angle count at time 2, the canopy is not dense, providing more light to the forest floor. The positive coefficients for the fluvisol (*SCD22*) soil group shows that on wetter sites more REGEN II will encroach. On the grass (*GVD12*) and the pioneer (*GVD17*) vegetation types the coefficients are negative. This shows the difficulty for REGEN II to appear on these sites. Conversely, on the hydrophytic perennial shrub ground vegetation type (*GVD19*) more REGEN II is expected to appear at time 2 compared to other vegetation types. The *OVERSH_T2* is a summation of the percent shares of *STANGSH_T2*, *BHISH_T2*, *BHIISH_T2* and *STARKSH_T2*. The negative coefficient shows that as density of the overstory increases, the less REGEN II will appear at time 2.

REGEN II – LARCH

If REGEN II *is predicted to be present at time 2, what quantity of this* REGEN II *will be larch.*

The positive coefficient for (*LA_JUNGIISH_T1*) shows that as the percent share of LARCH REGEN II at time 1 increases, more LARCH REGEN II will be present at time 2. The LARCH REGEN I variable, (*LA_JUNGISH_T1*) shows that when the regeneration is younger, as the percent share of LARCH REGEN I at time 1 increases, even more LARCH REGEN II will be present at time 2. This is correct since, REGEN II will grow into a POLE stand and REGEN I will grow into REGEN II. The positive coefficient for elevation (*ELEV*) shows that as elevation increases more LARCH REGEN II will be present. If the stand type is pure spruce (*STD1_T2*) or pure stone pine (*STD6_T2*), the negative coefficients show that less LARCH REGEN II will appear at time 2. If the soil group is leptosols derived from non-calcareous material (*SCD1*), then less LARCH REGEN II will be found. Conversely, on climate induced podzolic soil types (*SCD5*), more LARCH REGEN II will be found. If the ground vegetation type is subalpine dwarf shrub type (*GVD14*) or the pasture forest type (*GVD16*), the positive coefficients suggest that more LARCH REGEN II will be present at time 2.

REGEN II – BROADLEAVED TREES

If REGEN II *is predicted to be present at time 2, what quantity of this* REGEN II *will be broadleaved.*

The positive coefficient for logarithm(*BL_JUNGIISH_T1*) shows that as the percent share of BROADLEAVED REGEN II at time 1 increases, more BROADLEAVED REGEN II will be present at time 2. The BROADLEAVED REGEN I variable, logarithm(*BL_JUNGISH_T1*) shows that when the regeneration is younger, as the percent share of BROADLEAVED REGEN I at time 1 increases, even more BROADLEAVED REGEN II will be present at time 2. This is correct since, REGEN II will grow into a POLE stand and REGEN I will grow into REGEN II. The negative coefficient for elevation (*ELEV*) shows that as elevation increases less broadleaved regen II will be present. If the stand type is pure beech (*STD10_T2*), pure oak (*STD11_T2*), mixed deciduous (*STD41_T2*) or mixed coniferous (*STD40_T2*) then more broadleaved regen II, represented by their positive coefficients, will be present at time 2. In growth zones 3 (*GZD3*), 6 (*GZD6*), 10 (*GZD10*) and 19 (*GZD19*) the positive coefficients support the fact that these growth zones are predominantly deciduous. The negative coefficient for the substrate induced podzol soil group (*SCD6*) shows that on these soils, deciduous species are less prevalent. In the shade tolerant herb type (*GVD1*) and the depletion or litter erosion sites (*GVD13*) the positive coefficient shows that more broadleaved species will be present at time 2. Conversely, in the sparse moss type (*GVD6*) and the competing grass cover type (*GVD12*) it is expected that less broadleaved species will be present at time 2.

5.2.4 Wildlife Browse Classes

NO BROWSE - 1

If NO BROWSE *is present at time 1, in what quantity will it be present at time 2.*

The positive coefficient of logarithm *A_NOSH_T1* indicates that with an increasing percent share of NO BROWSE (areas completely void of browsable vegetation) at time 1, the more area at time 2 will have NO BROWSE. The positive coefficients for logarithm *JUNGIISH_T1* and *OVERSH_T2* (the summation of the percent shares of *STANGSH_T2, BHISH_T2, BHIISH_T2* and *STARKSH_T2*) shows that as density of the overstory increases, the more NO BROWSE will appear at time 2. The negative coefficient of *STD0_T2* indicates that if there are no trees in the angle count, the stand is not dense, allowing sufficient light to reach the forest floor for vegetation. The moss ground vegetation types (*GVD6* and *GVD7*) have positive coefficients. These two types represent a large group spanning the coniferous regions, therefore it is expected that coniferous regions would have more NO BROWSE, when compared to deciduous types. The *C_BA* variable has a positive coefficient suggesting that after harvesting there will be less NO BROWSE since opening up of the canopy allows for more understory vegetation. The pure Norway stand type (*STD1_T2*) and the pure Beech type (*STD10_T2*) both have positive coefficients indicating that compared to other stand types there will be more areas with NO BROWSE. In the climate induced podzol soil type (*SCD5*), the negative coefficient suggests that there will be less areas of NO BROWSE. The shade tolerant herb (*GVD1*) and the moderhumus in conifer stands (*GVD4*) both have positive coefficients indicating that there will be more areas with NO BROWSE in these vegetation types. Quadratic mean diameter at time 2 (*QMD_T2*) represents the age and size of the stand . The negative coefficient suggests that older stands have less areas of NO BROWSE.

NO BROWSE - 0

If NO BROWSE *is not present at time 1 (area is 100% browse), in what quantity will it be present at time 2.*

NO BROWSE when NO BROWSE is not present at time 1, indicates that all the area available for understory vegetation is fully occupied. The square of the elevation (*ELEV*) coefficient is negative indicating that as elevation increases, the less the area with NO BROWSE. This is as expected since growth is slower at higher elevations, so change will occur much slower. The variables *GVD1, GVD2, GVD4* and *GVD6* all have positive coefficients indicating that these have higher rates of change compared to other vegetation types. The square of *OVERSH_T2* is a summation of the percent shares of *STANGSH_T2, BHISH_T2* and *BHIISH_T2*, squared. This variable along with the square of REGEN II (*JUNGIISH_T1*) have positive coefficients showing that if an area is fully occupied at time 1, the more areas with NO BROWSE there will be at time 2, as the shares of these variable increase. Growth zones 15 (*GZD15*), 18 (*GZD18*) and 20 (*GZD20*) have positive coefficients indicating that in these regions, more areas of NO BROWSE will appear at time 2 compared to other regions. In *GZD9* the opposite is true. The positive coefficient for *STD1_T2* indicates that if the stand type is pure Norway spruce, more areas with NO BROWSE will appear, since spruce will quickly grow out of the browsable region and/or there is normally less browse below a spruce stand. This is the same for the square of *ASUNGSH_T1* which represents the sum of the *A_NDSH_T1, A_LBSH_T1* and *A_STSH_T1*, squared. These types are trees and shrubs which will also grow out of the browsable region. If their density is sufficient, no other browsable species will appear below, therefore more areas of NO BROWSE will appear. The variable GRASS BROWSE (*A_GRSH_T1*) has a negative coefficient which indicates that as the percent share of grass increases at time 1, the less areas with NO BROWSE will appear. This is intuitively correct since grass will not grow out of the browsable region and is a good competitor when compared to other browse species. The change in basal area (*C_BA*) coefficient is positive which suggests that after harvest there will be less areas with NO BROWSE when compared to a non harvest scenario. The positive coefficient for the eutric cambisol (*SCD3*) and the cambisols (*SCD10*), suggest that in these soil groups more areas of NO BROWSE will appear compared to other soil groups.

CONIFER BROWSE - 1

If CONIFER BROWSE *is present at time 1, in what quantity it will be present at time 2.*

The coefficient for the variable pure Norway spruce type (*STD1_T2*) is negative. The negative coefficient indicates that the area of CONIFER BROWSE present at time 2 will be lower. This is as expected since Norway spruce has a high juvenile conifer growth rate. The shade tolerant herb type (*GVD1*) is predominantly in growth zones 9 (*GZD9*) and 10 (*GZD10*) which are predominantly deciduous. In these cases the CONIFER BROWSE may be decreasing due to high competition with the beech. The square root of the NO BROWSE (*A_NOSH_T1*) variable has a negative coefficient suggesting that as the area of NO BROWSE increases, the area of CONIFER BROWSE decreases. With a more dense stand above, less CONIFER BROWSE is expected. The negative coefficients for variables REGEN II (*JUNGIISH_T1*) and the *OVERSH_T2* (summation of the POLE (*STANGSH_T2*) MATURE I (*BHISH_T2*) and MATURE II (*BHIISH_T2*)) indicates that as the density above becomes greater the less CONIFER BROWSE below. The eutric cambisols (*SCD3*), the spodi-cambisol (*SCD4*), the substrate induced podzols (*SCD6*), leptosols (*SCD17* and *SCD18*) and the chromic cambisols (*SCD19*) have positive coefficients suggesting that in these soil types more CONIFER BROWSE will be present at time 2. In the *SCD4* and *SCD6* it may also be that these soil types favour conifer species and therefore conifer regeneration. In growth regions 12, 17 and 18 (*GZD12, GZD17* and *GZD18*) the positive coefficients suggest that more CONIFER BROWSE will be present at time 2 compared to other growth regions. Conversely in growth zone 10 (*GZD10*) there are less areas with CONIFER BROWSE at time 2. This can possibly be explained by the competition with beech. The change in basal area (*C_BA*) coefficient is negative which suggests that after harvest there will be more CONIFER BROWSE at time 2, compared to a non harvest scenario. The positive coefficient for the square root of conifer browse (*A_NDSH_T1*) shows that as the percent of young conifer trees, REGEN I, increases, the more CONIFER BROWSE will be present at time 2.

CONIFER BROWSE – 0

If CONIFER BROWSE *is not present at time 1, in what quantity it will be present at time 2.*

Elevation (*ELEV*) coefficient is positive indicating that as elevation increases the more Conifer Browse at time 2 will be found. This is intuitively correct since conifer species are more common at higher elevations. The *STD0_T2* variable indicates that there are no trees in the angle count at time 2. The coefficient is positive which suggests that as density of the canopy decreases, there is more conifer encroachment onto the site. In growth regions 11, (*GZD11*), 12 (*GZD12*), 18 (*GZD18*) and 20 (*GZD20*) more conifer will encroach onto a site compared to all other regions. The shade tolerant herb type (*GVD1*) has a negative coefficient showing that competition is high with deciduous species. In the sparse moss type (*GVD6*) has a positive coefficient showing that more encroachment will occur in this primarily conifer vegetation type. The sparse moss type (*GVD6*), the *Calluna* type (*GVD10*), the pasture type (*GVD16*) and the seep (*GVD18*) vegetation types, the positive coefficients show that more CONIFER BROWSE encroachment will occur in these types. The negative coefficients for variables REGEN II (*JUNGIISH_T1*), *OVERSH_T2* (summation of POLE (*STANGSH_T2*), MATURE I (*BHISH_T2*), MATURE II (*BHIISH_T2*) and old growth (*STARKSH_T2*)) indicates that as the density above becomes greater the less CONIFER BROWSE will be found below. The square root of the NO BROWSE (*A_NOSH_T1*) variable has a negative coefficient suggesting that as the area of NO BROWSE increases the area of CONIFER BROWSE decreases.

DECIDUOUS BROWSE - 1

If DECIDUOUS BROWSE *is present at time 1, in what quantity it will be present at time 2.*

As the percent share of DECIDUOUS BROWSE present at time 1 increases, represented by the logarithm *A_LASH_T1*, the more DECIDUOUS BROWSE will be present at time 2. The elevation (*ELEV*) coefficient is negative indicating that as elevation increases, the less DECIDUOUS BROWSE will be found. This is intuitively correct since deciduous species are more common at lower elevations. The positive coefficients for growth zone 6 (*GZD6*), 9 (*GZD9*) and 10 (*GZD10*) identifies the primarily deciduous growth zones. The positive coefficients for growth zone 14 (*GZD14*) suggests that more DECIDUOUS BROWSE at time 2 will be found in this growth zone compared to others. The coefficient for soil group 11 (*SCD11*) is positive. This soil type is found in the flysch zone of Austria overlapping growth zones 7 and 8. These soils are heavy in nutrients supporting primarily deciduous species. Conversely, the pure Norway spruce type (*STD1_T2*) has a negative coefficient. The *A_NOSH_T1* variable has a negative coefficient suggesting that as the area of NO BROWSE increases the area of DECIDUOUS BROWSE decreases. The coefficient for the soil group dystric cambisols (*SCD2*) is negative suggesting that in this type, if DECIDUOUS BROWSE is found at time 1, less DECIDUOUS BROWSE will be found at time 2. The opposite is true for the spodi-dystric cambisols (*SCD4*). The change in basal area (*C_BA*) coefficient is negative which suggests that after harvesting there will be more DECIDUOUS BROWSE present at time 2, compared to a non harvest scenario. The negative coefficients for variables, REGEN II squared (*JUNGIISH_T1*), and *OVERSH_T2* (summation of POLE (*STANGSH_T2)* AND MATURE I (*BHISH_T2*)) indicates that as the density above becomes greater the less DECIDUOUS BROWSE will be found below.

DECIDUOUS BROWSE – 0

If DECIDUOUS BROWSE *is not present at time 1, in what quantity will it be present at time 2.*

The elevation (*ELEV*) coefficient is negative indicating that as elevation increases, the less DECIDUOUS BROWSE will be found. This is intuitively correct since deciduous species are more common at lower elevations. The *A_NOSH_T1* variable has a negative coefficient suggesting that as the area of NO BROWSE increases the less DECIDUOUS BROWSE will be found at time 2. The negative coefficient of the pure Norway spruce type (*STD1_T2*) shows that less deciduous species will encroach in this type. Conversely, if the stand type is pure beech or mixed deciduous the more it will encroach. This is illustrated by the positive coefficients for *STD10_T2* and *STD41_T2*. In the shade tolerant herb type (*GVD1*), the moderately moist herb type (*GVD2*), thermophilic herb types (*GVD3*), and the hydrophytic perennial shrub type (*GVD19*) the coefficients are positive. All these vegetation types support deciduous species. Unexpectedly, the moderhumus type (*GVD4*) is also positive. In growth zones 1 (*GZD1*) and 4 (*GZD4*) less DECIDUOUS BROWSE will encroach onto a site, illustrated by the negative coefficient. This is probably due to the acidic soils in these regions. In the primarily deciduous growth zones 6 (*GZD6*), 7 (*GZD7*), 8 (*GZD8*) and (*GZD10*) the coefficients are positive. In growth zone 9 (*GZD9*) the coefficient is negative showing the significance of the beech in this spruce-fir-beech forested area. The change in basal area (*C_BA*) coefficient is negative which suggests that after harvesting more DECIDUOUS BROWSE will be present at time 2, compared to a non harvest scenario.

SHRUB BROWSE – 1

If SHRUB BROWSE *is present at time 1, in what quantity will it be present at time 2.*

As the percent share of logarithm SHRUB BROWSE (*A_STSH_T1*) present at time 1 increases, the positive coefficient shows that more SHRUB BROWSE will be present at time 2. The *ELEV* coefficient is negative indicating that as elevation increases, the less SHRUB BROWSE will stay on the site. The *A_NOSH_T1* variable has a negative coefficient suggesting that as the area of NO BROWSE increases the less SHRUB BROWSE will be present at time 2. This is also the case with the REGEN II (*JUNGIISH_T1*) variable which has a negative coefficient. The spodi-dystric cambisols (*SCD4*) has a negative coefficient which supports that the SHRUB BROWSE prefer less acidic soil types. In the heavy texture cambisols (*SCD9*) and the temporarily waterlogged soils (*SCD13*) the negative coefficient suggest that SHRUB BROWSE will decrease in quantity at time 2. Conversely in the light textured cambisols (*SCD8*) more SHRUB BROWSE will be found at time 2. The negative coefficient for the hydrophytic perennial shrub type (*GVD19*) represents very wet sites which SHRUB BROWSE does not prefer. The negative coefficient for the moderhumus in conifer type (*GVD4*) shows that SHRUB BROWSE will decrease in quantity. In growth zone 20 (*GZD20*) the negative coefficient suggests that less SHRUB BROWSE will be present at time 2.

SHRUB BROWSE – 0

If SHRUB BROWSE *is not present at time 1, in what quantity will it be present at time 2.*

The *ELEV* coefficient is negative indicating that as elevation increases, the less SHRUB BROWSE will encroach on to the site. In growth zones 2(*GZD2*), 3(*GZD3*), *GRP_GZ* (13(*GZD13*), 14(*GZD14*), 15(*GZD15*) and 18 (*GZD18*)) the coefficients are positive which shows that in these growth zones more SHRUB BROWSE will encroach onto a site than in other growth zones. Conversely, in growth zones 8(*GZD8*), 9(*GZD9*) and 10 (*GZD10*) the coefficients are negative. The negative coefficient for the pure beech type (*STD10_T2*) is supported by the behaviour shown for growth zones 8, 9 and 10. Beech is a good competitor not allowing for encroachment by the shrub species. The positive coefficient for the black pine (*STD5_T2*) and the oak (*STD11_T2*) stand types suggests that SHRUB BROWSE is favoured in these stand types. In the cambisols derived from calcareous material (*SCD10*) and the fluvisols along small rivers (*SCD21*) the positive coefficients suggest that encroachment of shrubs is higher. The negative coefficient for one layer stands (*SSD1*) shows that there is less encroachment of shrubs in these stands compared to two or multilayer stands. The positive coefficient for the shade tolerant herb type (*GVD1*), the thermophilic herb type (*GVD3*), the subapline dwarf shrub type (*GVD14*) the hydrophytic herb type (*GVD19*) and the floodplain type (*GVD20*) shows that these vegetation types support the shrubs that make up SHRUB BROWSE. Inversely, the moss types (*GVD6* and *GVD7*) do not support these species. The positive coefficients for the southeast aspect (*ASD4*) and the south west aspect (*ASD6*) shows that the species of shrubs listed prefer sunny, drier locations. The *A_NOSH_T1* variable has a negative coefficient suggesting that as the area of NO BROWSE increases the less SHRUB BROWSE will encroach. The change in basal area (*C_BA*) coefficient is negative suggesting that after harvesting more SHRUB BROWSE will be present at time 2, compared to a non harvest scenario.

RASPBERRY BROWSE– 1

If RASPBERRY BROWSE *is present at time 1, in what quantity will it be present at time 2.*

As the percent share of RASPBERRY BROWSE (*A_HISH_T1*) present at time 1 increases, the positive coefficient shows that more RASPBERRY BROWSE will be present at time 2. The *ELEV* coefficient is negative indicating that as elevation increases, less raspberry will be present at time 2. This is intuitively correct since raspberry is more common at lower elevations. The *A_NOSH_T1* variable has a negative coefficient suggesting that as the area of NO BROWSE increases the less RASPBERRY BROWSE will be present at time 2. This is also the case with the variable *JUNGHSH_T1* which also has a negative coefficient. The negative coefficient for the pure Norway spruce stand type (*STD1_T2*) indicates that less raspberry will be present under a spruce stand compared to other stand types. Conversely, under pure Scots pine stands (*STD4_T2*) more raspberry will be found. The coefficients for the stagnic cambisols (*SCD14*), the leptosols (*SCD17* and *SCD18*) and Fluvisols (*SCD22*) are negative. Leptosols are weakly developed soils, low in nutrients which are unfavourable for raspberry. The coefficients for the moderhumus vegetation type (*GVD4*) and the hydrophytic perennial shrub type (*GVD19*) are positive showing raspberries preference for the conditions in these vegetation types. In growth zone 1 (*GZD1*) and 4 (*GZD4*) the positive coefficient suggests that more RASPBERRY BROWSE will be present at time 2.

RASPBERRY BROWSE– 0

If RASPBERRY BROWSE *is not present at time 1, in what quantity will it be present at time 2.*

The *ELEV* coefficient is negative indicating that as elevation increases, the less RASPBERRY BROWSE will encroach. This is intuitively correct since raspberry is more common at lower elevations. The *STD0_T2* variable indicates if the subplot has no trees in the angle count at time 2. The positive coefficient shows that if the overstory of a stand is not very dense, more raspberry will encroach onto the site. Similarly, the coefficients for the shade tolerate herb type (*GVD1*), the moderhumus vegetation type (*GVD4*), the hydrophytic perennial shrub type (*GVD19*) and the floodplain (*GVD20*) are positive showing raspberries preference for the conditions in these vegetation types. In growth zones 1(*GZD1*), 2(*GZD2*), 3(*GZD3*), 4(*GZD4*), 7(*GZD7*), 19(*GZD19*), and 21(*GZD21*) the coefficients are positive showing that in these growth zones more RASPBERRY BROWSE will encroach onto a site than in other growth zones. In the heavy texture cambisols (*SCD9*), the planosols from loess (*SCD11*) and the temporarily water logged soils (*SCD13*) the positive coefficient shows that raspberry will encroach more than compared to other soils. In the substrate-induced podzols (*SCD6*), the leptosols (*SCD17* and *SCD18*) the chromic cambisols (*SCD19*), the gleysols (*SCD20*) and the fluvisols along small rivers (*SCD21*) the negative coefficient shows that in these soils less raspberry will encroach. The *A_NOSH_T1* variable has a negative coefficient suggesting that as the area of NO BROWSE increases the less RASPBERRY BROWSE will encroach. This is also the case represented by the negative coefficients for variables REGEN II (*JUNGIISH_T1*), *OVERSH_T2* (summation of POLE (*STANGSH_T2),* MATURE I (*BHISH_T2*) and MATURE II (*BHIISH_T2*)). The change in basal area (*C_BA*) coefficient is negative suggesting that after harvesting more RASPBERRY BROWSE will be present at time 2, compared to a non harvest scenario.

BLUEBERRY BROWSE - 1

If BLUEBERRY BROWSE *is present at time 1, in what quantity will it be present at time 2.*

The variable logarithm *A_HESH_T1* has a positive coefficient, which suggests that as the percent share of blueberry at time 1 increases, the more blueberry will be present at time 2. Elevation (*ELEV*) has a positive coefficient, which is intuitively correct, since we expect blueberry to favour higher altitudes. The slope coefficient (*SLPE*) is negative suggesting that as slope increases, the less blueberry will stay on the site. The main reason may be that on steeper slopes the sites may be dryer. In the pure Norway spruce sites (*STD1_T2*) the negative coefficient shows that blueberry will decrease in quantity at time 2. The *STD0_T2* variable indicates if the subplot has no trees in the angle count at time 2. The negative coefficient shows that if the overstory of a stand is not very dense, blueberry will disappear from the site which, is intuitively correct since blueberry prefers shade. The negative coefficient for variable *POLE* (*STANGSH_T2)* suggests that although blueberry prefers shade, as a pole stand becomes denser, it becomes too dark, even for blueberry. The change in basal area (*C_BA*) coefficient which is positive suggests that after harvesting, less

BLUEBERRY BROWSE will be present at time 2, compared to a non harvest scenario. In growth region 17 (*GZD17*), less blueberry will stay compared to other growth regions. If the soil group is dystric cambisols (*SCD2*) or the substrate induced podzols (*SCD6*), the less blueberry will be present at time 2, in comparison to other soil types. The coefficients for the shade tolerant and moderately moist herb types (*GVD1* and *GVD2*), the moderhumus in conifer stands type (*GVD4*) the competing grass cover type (*GVD12*), the seep vegetation type (*GVD18*) and the hydrophytic perennial herb type (*GVD19*) are all negative. This suggests that if blueberry is present on these sites at time 1, it will be less prominent at time 2.

BLUEBERRY BROWSE- 0

If BLUEBERRY BROWSE *is not present at time 1, in what quantity will it be present at time 2.*

Elevation (*ELEV*) has a positive coefficient which is intuitively correct, since we expect blueberry to favour higher altitudes. The slope coefficient (*SLPE*) is negative suggesting that as slope increases, the less blueberry will encroach onto the site. The sparse moss ground vegetation type (*GVD6*) is a blueberry type therefore it is expected that more blueberry will encroach onto this site. The subalpine dwarf shrub type (*GVD14*), includes blueberry as a species, therefore, it is expected that blueberry will encroach onto this site. This is supported by the positive coefficient. The positive coefficients for the northeast aspect (*ASD2*) and the northwest aspect (*ASD8*) shows that blueberry prefers shaded locations. The negative coefficient for the mixed deciduous stand type (*STD41_T2*) indicates less blueberry will encroach onto a site when it is mixed deciduous. The percent share of REGEN I at time 1, squared, (*JUNGISH_T1*) has a negative coefficient. This shows that as the percent share of REGEN I increases, the less blueberry will encroach onto the site. This shows that blueberry is in direct competition with REGEN I and is not the better competitor. The *STD0_T2* variable indicates if the subplot has no trees in the angle count at time 2. The positive coefficient shows that if the overstory of a stand is not very dense, more blueberry will encroach onto the site than if it is dense. The coefficient for the moderhumus type (*GVD4*) is negative suggesting that less blueberry will encroach onto this vegetation type compared to others.

ERICA BROWSE - 1

If ERICA BROWSE *is present at time 1, in what quantity will it be present at time 2.*

The variable *A_ERSH_T1* has positive coefficient, which suggests that as the percent share of ERICA BROWSE at time 1 increases, the more *Erica* will be present at time 2. The negative coefficient for water regime (*WTRG*) shows that as the site becomes wetter the less ERICA BROWSE will stay on the site. Coefficients for the variable representing growth zones 1 (*GZD1*) and 20 (*GZD20*) are negative, showing that less ERICA BROWSE will be present at time 2. Conversely, in growth zones 14 (*GZD14*) and 17 (*GZD17*) more ERICA BROWSE will appear. The *Erica* ground vegetation type (*GVD15*) is an "*Erica*" type therefore it is expected that more *Erica* will appear compared to other ground vegetation types. More *Erica* will also appear in the *Calluna* ground vegetation type (*GVD10*). The *A_NOSH_T1* variable has a negative coefficient suggesting that as the area of NO BROWSE increases the less ERICA BROWSE will be present at time 2. This is also the case with the variable *JUNGIISH_T1*, which also has a negative coefficient.

HERB BROWSE - 1

If HERB BROWSE *is present at time 1, in what quantity will it be present at time 2.*

The variable logarithm *A_KRSH_T1* has a positive coefficient, which suggests that as the percent share of HERB BROWSE at time 1 increases, the more HERB BROWSE will be present at time 2. The positive coefficient for the water regime (*WTRG*) shows that as sites become wetter there will be more HERB BROWSE at time 2. The positive coefficients for the mixed coniferous and deciduous types (*STD40_T2* and *STD41_T2*) shows that more HERB BROWSE will appear in these stand types compared to the others. The spodi-dystric cambisol soil group (*SCD4*) has a negative coefficient suggesting that the herbs in the HERB BROWSE class do not favour this soil type. The negative coefficients for the moss ground vegetation types (*GVD5* and *GVD6*), the *Avenella* type (*GVD8*) and the *Erica* type (*GVD15*) show that herbs, if present in these types at time 1, will be less prominent at time 2, compared to other types. In growth zones 1 and 4 (*GZD1* and *GZD4*) the coefficients are also negative. For growth zones 9(*GZD9*), 10 (*GZD10*), 12 (*GZD12*) and 17 (*GZD17*) coefficients are positive, showing that more herbs will be present at time 2 compared to other zones. The positive coefficient for the quadratic mean diameter at time 2 (*QMD_T2*) shows that as stands become older, the more HERB BROWSE will be found on these sites. The negative coefficient for percent share of REGEN I (*JUNGISH_T1*) and REGEN II (*JUNGIISH_T1*) at time 1 shows that as the amount of these two growth classes increases, the less HERB BROWSE will be present at time 2.

HERB BROWSE- 0

If HERB BROWSE *is not present at time 1, in what quantity will it be present at time 2.*

The positive coefficients for the mixed deciduous type (*STD41_T2*) shows that more HERB BROWSE will encroach in this stand type compared to the others. In growth zone 1 (*GZD1*) the coefficient is also negative suggesting that less HERB BROWSE will encroach onto a site. The coefficients for the shade tolerant herb type (*GVD1*), the moderately moist herb type (*GVD2*), the pasture (*GVD16*), the seep vegetation type (*GVD18*) and the hydrophytic perennial shrub type (*GVD19*) are all positive. These are either herb types or areas that herbs favour, therefore, it is expected that more herbs will encroach onto these sites. Conversely, the two moss types (*GVD5* and *GVD6*) have negative coefficients showing the dislike of these types by herbs. The *A_NOSH_T1* variable has a negative coefficient suggesting that as the area of NO BROWSE increases the less HERB BROWSE will encroach onto a site. The coefficients for the eutric cambisols (*SCD3*), the stagnic gleysols (*SCD14*), the leptosols (*SCD17* and *SCD18*), the chromic cambisols (*SCD19*), and the fluvisols (*SCD21* and *SCD22*) are all positive showing that HERB BROWSE encroachment is favoured on these soil types. The change in basal area (*C_BA*) coefficient is positive suggesting that after harvest less HERB BROWSE will encroach at time 2, compared to a non harvest scenario. The positive coefficient for the quadratic mean diameter at time 2 (*QMD_T2*) shows that as stands become older, the more herbs will encroach.

FERN BROWSE - 1

If FERN BROWSE *is present at time 1, in what quantity will it be present at time 2.*

The variable logarithm *A_FASH_T1* has a positive coefficient which suggests that as the percent share of FERN BROWSE at time 1 increases, the more FERN BROWSE will be present at time 2. The positive coefficient for water regime (*WTRG*) shows that as the site becomes wetter the more FERN BROWSE will appear on the site. Elevation (*ELEV*) has a positive coefficient, which suggests that FERN BROWSE favours higher altitudes. The negative coefficient for the southeast (*ASD4*), south

(*ASD5*) and the southwest (*ASD6*) facing slopes shows that FERN BROWSE dislikes hotter, drier aspects. From the positive coefficient of the moderhumus ground vegetation type (*GVD4*), it can be seen that ferns prefer this vegetation type. Conversely, the more competitive, grass cover type (*GVD12*) has a negative coefficient showing the ferns inability to compete with grasses. For growth zones 1 (*GZD1*), 4 (*GZD4*), 8 (*GZD8*) and 12 (*GZD12*) the coefficients are positive showing that if ferns are present at time 1 in these zone, the more FERN BROWSE will be expected at time 2 compared to other zones. Conversely, for growth zone 17 (*GZD17*) the less FERN BROWSE will be present at time 2. The positive coefficient for the quadratic mean diameter at time 2 (*QMD_T2*) shows that as stands become older, the more FERN BROWSE will appear at time 2. The old growth stand type (*STARKSH_T2*) also has a positive coefficient showing the preference of older stands by FERN BROWSE.

FERN BROWSE - 0

If FERN BROWSE *is not present at time 1, in what quantity will it be present at time 2.*

The positive coefficient for water regime squared (*WTRG*) shows that as the site becomes wetter the more FERN BROWSE will encroach onto a site. The positive coefficient for the pure Norway spruce type (*STD1_T2*) indicates that FERN BROWSE prefers this type over other types. The positive coefficient for the north (*ASD1*), northeast (*ASD2*) and the northwest (*ASD8*) facing slopes shows ferns preference for shady aspects. The positive coefficient for the quadratic mean diameter at time 2 (*QMD_T2*) shows that as stands become older, the more FERN BROWSE will encroach onto a site. From the positive coefficient of the moderhumus ground vegetation type (*GVD4*), the moderately moist herb type (*GVD2*) and the shrub type (*GVD19*), it can be seen that more FERN BROWSE will encroach onto these sites compared to other types. The coefficients for the stagnic gleysols (*SCD14*) and the spodi-dystric cambisols (*SCD4*) are positive indicating that more FERN BROWSE will encroach onto sites compared to others. The coefficients for growth zone 8 (*GZD8*), 11 (*GZD11*) and 12 (*GZD12*) are all positive. This indicates that in these growth zones more FERN BROWSE will encroach. Conversely, in growth zones 1 (*GZD1*), 3 (*GZD3*), 18 (*GZD18*) and 20 (*GZD20*) the opposite is true. The square of the NO BROWSE (*A_NOSH_T1*) variable has a negative coefficient suggesting that as the squared percent area of NO BROWSE increases the less FERN BROWSE will encroach onto a site.

GRASS - 1

If GRASS BROWSE *is present at time 1, in what quantity will it be present at time 2.*

The logarithm A_GRSH_T1 has a positive coefficient which shows that as the percent share of grass at time 1 increases, the more grass will be present at time 2. Elevation (*ELEV*) has a positive coefficient, which suggests that grass is a better competitor at higher elevations. The negative coefficients for REGEN II (*JUNGIISH_T1)* and Pole (*STANGSH_T2*) shows that as the density of these growth classes increases, the less grass will stay on the site. The change in basal area (*C_BA*) coefficient is negative suggesting that after harvesting more grass will be present at time 2, compared to a non harvest scenario. The positive coefficient for the leptosol soil group (*SCD17*) shows grasses strength as a competitor on poor sites when there is less competition from above. The negative coefficient for the eutric cambisols (*SCD3*) shows that on very basic sites, grass is less of a competitor. In the moist herb vegetation type (*GVD2*), the thermophilic herb type (*GVD3*), the *Avenella* type (*GVD8*), *Sphagnum-Vaccinium-Avenella* type (*GVD11*), the grass type (*GVD12*), the depletion types (*GVD13*), the *Erica* type (*GVD15*), the pasture type (*GVD16*), the seep vegetation type (*GVD18*) and the floodplain type (*GVD20*) the coefficients are positive suggesting that grass is a good competitor in these types compared to other vegetation types. In growth zone 1 (*GZD1*) the coefficient is positive indicating that grasses compete well in this zone. Conversely, in growth zone 11 (*GZD11*), 16 (*GZD16*), 18 (*GZD18*) and 20 (*GZD20*) grasses are not as competitive as shown by the negative coefficient.

GRASS – 0

If GRASS BROWSE *is not present at time 1, in what quantity will it be present at time 2.*

Elevation (*ELEV*) has a positive coefficient which suggests that grass will encroach more at higher elevations. The *STD0_T2* variable indicates the subplot has no trees in the angle count at time 2. The positive coefficient shows that if the overstory of a stand is not very dense, more grass will encroach onto the site. In pure Norway spruce stands (*STD1_T2*) and in the pure larch stands (*STD3_T2*), the positive coefficients show that more grass will encroach in these stand types compared to other types. Conversely, in pure beech stand types (*STD10_T2*) the negative coefficient shows that less grass will encroach onto a site. The negative coefficients for logarithm REGEN II (*JUNGIISH_T1)* and logarithm Pole (*STANGSH_T2*) shows that as the amount of these growth classes increases, the less grass will encroach onto a site. The square root of the *A_NOSH_T1* variable has a negative coefficient suggesting that as the area of NO BROWSE increases the less GRASS BROWSE will encroach. The change in basal area (*C_BA*) coefficient is negative suggesting that after harvesting more grass will encroach onto a site, compared to a non harvest scenario. In the *Avenella* (*GVD8*), the competing grass (*GVD12*), the pasture (*GVD16*) and the seep (*GVD18*) ground vegetation types, the coefficients are positive as expected. In the moderhumus type (*GVD4*) the coefficient is negative showing grasses less competitive nature in this vegetation type. In growth zone 1 (*GZD1*) the coefficient is positive showing that more grass will encroach in this zone compared to other growth zones. In growth zone 17 (*GZD17*) the opposite is true.

5.3 Other Uses for the Models Developed

The wildlife browse classes according to the ANFI, were chosen because of their applicability to a range of wildlife species, not just roe deer. Although the models in this study were developed implicitly to meet the objective of predicting the future habitat suitability indices for roe deer, there is nothing to suggest that the models are not valuable in the management of other species like red deer or chamois. Use of these models for the management of other wildlife resources is certainly possible.

Species response models, as discussed earlier in section 1.1, are developed on data representing one moment in time. Therefore, through the use of large samples, a relationship, using environmental gradients, such as elevation, slope, aspect and the forest cover type can be made with the understory vegetation. The assessment of the future understory vegetation is made solely on the future forest stand projected by the growth model, since elevation, slope and aspect are not dynamic. Figure 5-1a illustrates this methodology. This methodology is practical when the sole intention is to obtain a map of the future distribution of a species. However only broad statements concerning vegetation dynamics can be made. The logistic models developed in this study are complex species response models, such that they take into consideration the presence/absence and abundance of the species at time 1 and are sensitive and responsive to changes in the forest structure. More specifically, these models take into consideration "how" the vegetation changes. Figure 5-1b illustrates this methodology. Therefore, as the future unfolds through simulation, the dynamics of the vegetation is modelled one step at a time. At each step, the condition of the vegetation at time 1 is known. Vegetation prevalence will change upwards and downwards as the forest stand undergoes change. The more severe the changes the greater the change to the vegetation will be. To test this in application, one could follow two different management strategies which result in the same future forest (time 2). The "species response models" would be deterministic, since prior management does not effect the prediction of future understory vegetation. Using the models developed in this study, one would expect the future understory vegetation to be different.

For these reasons, the models developed in this study are appropriate to study the effects of forest restoration, but not only with respect to roe deer. The future effects of restoration strategies on the understory vegetation could provide vital information for many different disciplines, not only for wildlife ecologists.

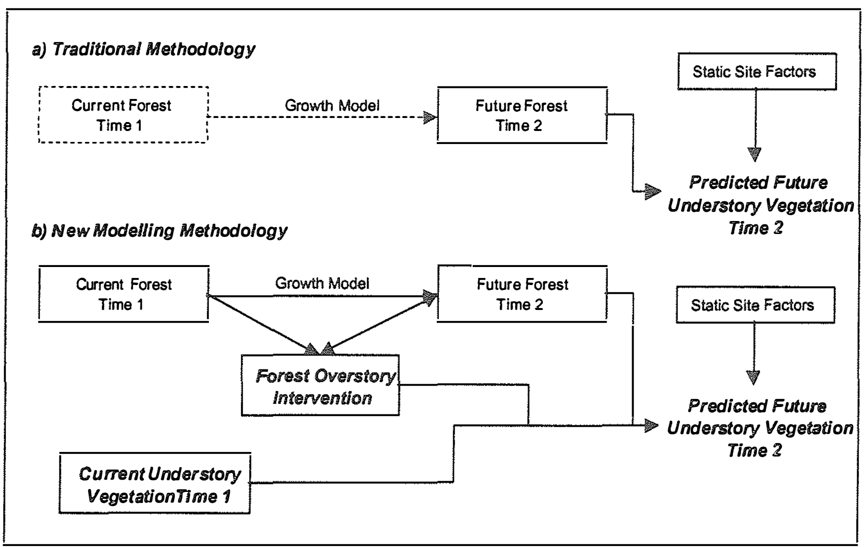


Figure 5-1: a) illustrates the inputs that are used in predicting future understory vegetation using traditional methodologies such as species response modelling. b) illustrates the inputs used in this study.

Abbildung 5-1: a) Zeigt die Größen, die traditionell zur Schätzung der Vegetation der Kraut- und Strauchschicht verwendet werden. b) Zeigt die Größen, die in dieser Studie verwendet werden.

Another promising use for the models developed in this study is for forest practitioners. For example the models could be used in forest management. The competition between trees, understory species and forest regeneration is well known. Forest practitioners, using simulation, could identify and pursue those management strategies which decrease competition with regeneration. Another example is if browsing of regeneration is a problem, management strategies which create understory vegetation in areas away from the regeneration areas, easing the negative effects of ungulate browsing. Forest practitioners should view the models as a tool that could be used to demonstrate the pros and cons of different management strategies.

In the context of Austrian growth modelling, there is another potential use for the growth class models, REGEN I and REGEN II. There is tremendous effort being made in modelling the growth of regeneration. The reason for this is, that most individual tree models have a minimum age or size of a tree before it can be simulated. PROGNAUS for example begins at a 5.0cm diameter at breast height. Up until this size, another model is required to provide PROGNAUS with the information concerning ingrowth, those trees crossing the 5.0cm threshold. The current approach in PROGNAUS to determine ingrowth, is to use the method posed by Ledermann et al. (In preparation). This modelling approach, determines the probability of trees in a plot appearing above the minimum diameter at breast height (DBH) of 5.0cm. If it is determined that trees will appear, their number is predicted using logarithmic regression, their species are predicted using a logit-function and their DBHs are predicted using a weibull distribution function. These models use basal area, crown competition factor, quadratic mean diameter, soil type, elevation, slope, the species of the overstory and the presence/absence of REGEN II at time 1 as inputs. However there is no model to estimate if REGEN II is present or absent in the future, once projections begin. The current work centres around determining if there is more than 10% basal area that is less than 10.4cm (upper threshold for the Regen II class). With some small modifications, for example, it should be possible to refit the REGEN I and REGEN II models using only a select set of variables, and to predict the probability of future REGEN II for use with the ingrowth models. This should improve estimates of ingrowth. There is also the potential to refit the ingrowth model with information regarding the percent share of REGEN II at time 1, given that this study quantifies this value. Also, there is an opportunity to see if the addition of information about REGEN I could improve the ingrowth models. The efforts to refit them would be interesting.

The possible uses for the models developed, as presented above, are to say the least, excellent opportunities to further the research in three entirely different disciplines: vegetation modelling, wildlife habitat modelling and growth modelling.

5.4 Future Model Development

During the development of the models and the modelling strategy used in this study, there was an opportunity to evaluate both the strengths and weaknesses of the models and modelling strategies. The most obvious limitation, which could have been significantly improved in the models was the class structure of the wildlife browse classes. The 10% classes are appropriate, since it surpasses the needed resolution for most wildlife applications. However, during the process of fitting the models, there were many instances where illogical outcomes occurred. An example is the case where the observed appearance of blueberry went from 0% at time 1 to 70%, in a 5 year period. The model predicted that at time 2, there was no blueberry. This is possible in extreme cases, but normally, we would not expect blueberry to encroach onto a site with such vigour. In fact, it is almost certain, that blueberry was on the site at time 1. The problem is the resolution of the inventory. The 10% classes are not sensitive to the low values. In other vegetation inventories, used for wildlife purposes, there are classes that allow for the identification of single plants and species with low percentages. This would have been very useful in the modelling process. Just the presence of a plant, under the right conditions, could be the difference in the model predicting correctly.

Another interesting problem deals with the NO BROWSE, wildlife browse class. It was used in the models as a measure of stand density, and was an important finding, even though the ANFI had a similar variable, the "degree of closure" (Schlussgrad). This variable measured the total stand closure, including the shrub layers. However, this variable could not be used for two reasons. First, it was not available in the area where the model validation was to be done and second, the degree of closure represented the future expected closure of the REGEN I and REGEN II classes, not the current. In the early stages of modelling, it was a dominant variable and was reluctantly removed. What is needed in the inventory though, is a variable that measures the density of the stand at 3 vertical points, perhaps at 0.7m, 1.3m and 3.0m. This could significantly improve the models.

6 CONCLUSIONS

The main objective of this study was to develop empirical understory vegetation models to aid in the prediction of future wildlife habitat suitability indices for roe deer as proposed by Reimoser and Zandl (1994). This objective was achieved through:

- the development of 26 logistic regression models which determine the probability of the different understory vegetation types being present or absent in the future.

- the development of 25 logarithmic regression models which quantify the future vegetation, if the logistic model predicts that it will be present in the future.

The major conclusions that can be drawn from this study can be divided into two categories, those that relate to the technical aspects of model development and those that relate to the significance of the models developed.

From a technical perspective, the use of a two model hierarchical modelling strategy functioned well. A logistic model was used to predict the probability of vegetation being present in the future. If it was determined to be present in the future, a logarithmic model was used to quantify it. The logistic models modelled the simple present or absent case, therefore the model fits were good. It was also found, that in application, the best cutoff value was at a probability level where the ratio, between those observations predicted to be present in the future over the total number of observations, was the same as the a priori probability. This was important because this distribution was essential in application and was a criteria in evaluating model performance. The logarithmic models were only needed if the logistic model determined that the vegetation type was present in the future. This meant that the logarithmic model could be fit on a reduced dataset. It was found that the best fits for the logarithmic models were obtained when a reduced dataset, made up of the *„correctly predicted“* observations from the logistic model, were used for model fitting. This was, firstly, because the observations with the greatest residuals were removed by the logistic model and secondly, because the models fit using this dataset, had intercepts closer to zero.

From the logistic modelling perspective, there is difficulty in choosing one model over another. The Hosmer and Lemeshow test statistic, $\hat{C}$, that is useful in evaluating goodness-of-fit cannot, however, be used to determine if one model performs better than another, when both models fit. In these cases, the area under the receiver operating characteristics (ROC) curve can be used. The area below ROC curves also allow for logistic regression models from other studies to be compared, since they measure a logistic models ability to discriminate, independent of species prevalence and the cutoff value.

The models developed in this study show that understory vegetation is not independent of its surroundings. This means that potentially, all vegetation types could be modelled. Each of the models developed are unique in form, which shows that each vegetation type is unique in the factors that dictate its existence. The fact that the paired logistic and the logarithmic models were made up of similar coefficients, with the same sign (+ or -), shows that the factors that determine probability of vegetation being present or not, in the future, also dictate how much of that vegetation will be present. From this study, the variables representing the status of the vegetation at time 1 were dominant in the models. This suggests that in general, vegetation is stabile, such that in a 5 or 6 year period, major changes in vegetation are not expected. However, large changes in vegetation can be expected if there are significant changes in its surrounding environment. This is supported by the dominance of the explanatory variables, change in basal area and change in quadratic mean diameter. These variables show that much of the vegetation change is driven by changes in the overstory density. Thus, many of the traditional forest management practices such as clear cutting and thinning, will have an effect on understory vegetation. One therefore can conclude that there will be an impact on the vegetation if restoration measures are pursued, and if there are vegetation changes, there will be an impact on ungulates like roe deer. These statements are not new, it has been known for a long time that these relationships exists. Although this may be true, until now, no one has taken advantage of this information in modelling understory vegetation. The information regarding the condition of the vegetation from time 1 as well as the change in the overstory forest are key pieces of information needed to successfully model understory vegetation change.

The primary use of the models developed in this study was to aid in determining the impacts of management strategies, like restoration on roe deer. In application, this can be done by first predicting the future forest stand conditions, under some proposed management strategy, using a growth model. Then using this future forest stand information, to predict the future understory vegetation using the models developed in this study. These understory vegetation predictions, along with the growth model predictions, can then be translated into the parameters which make up the habitat suitability indices. Through simulation, different management strategies can be tested and evaluated. In the end, a management strategy, that results in an acceptable balance between management objectives, even those that are conflicting, can be found and implemented.

7 SUMMARY

Forest ecosystem restoration will not only change the vegetative composition of the forest stand but also the composition and dynamics of the understory herb, forb and shrub layers. These changes will effect the use of these stands by ungulates by altering their habitat. In order to meet the requirements of sustainable resource management, it is necessary to assess and understand the future effects of forest management practices such as restoration. In Austria, Habitat Suitability Indices (HSI) for roe deer have been developed by Reimoser and Zandl (1994). These indices, for a given moment in time, measure a forest stands predisposition for use by roe deer. One method of determining the effects of restoration is to predict and evaluate *future* wildlife habitat indices, under different restoration strategies. For forest stands over a given diameter, future forest overstory conditions can be predicted using a growth model. However, this information is insufficient to calculate the future habitat suitability indices. The objective of this project was to develop empirical vegetation models to predict the change of understory vegetation over time. The vegetation types modelled are those which are needed to calculate the future HSI for roe deer.

Using the Austrian National Forest Inventory, a hierarchical, two model approach was used. First, using logistic regression, the probability of the vegetation type being present or absent in the future was predicted. Then, if the vegetation type was predicted to be present in the future, it was quantified using logarithmic regression. During the fitting of the models, several technical aspects concerning the model input datasets were tested. It was found that for the logarithmic models, a reduced dataset, made up of the correctly predicted observations from the logistic models had better fits and predicted distributions closer to the observed distributions. It was also found that the best cutoff value, needed for the logistic models, was the probability where the a priori probability was found in the predicted data. The modelling strategy presented is unique because; 1) it is modelling the change of vegetation over time, and 2) it incorporates variables from both the current forest and the future forest, understanding that in application, the future forest stand can be predicted using a growth model. A total of 26 logistic models and 25 logarithmic models were fit. It was found that the current condition of the vegetation type was an important explanatory variable in predicting its future condition. It was also found that changes

in the forest overstory density, represented by explanatory variables such as change in basal and change in quadratic mean diameter were also important in describing the change in the understory vegetation over time. Relating these results to forest restoration, it can be concluded that forest restoration will have a large impact on understory vegetation, which will be translated into a large impact in roe deer habitat. In application, the models developed in this study can be used in conjunction with a growth model, to evaluate different management strategies by predict future understory vegetation and future HSI.

8 ZUSAMMENFASSUNG

Waldsanierungsmaßnahmen ändern nicht nur die Zusammensetzung der Baumschicht, sondern auch die Artenzusammensetzung und die Dynamik der bodennahen Waldvegetation bis zur Strauchschicht. Diese Änderungen beeinflussen jedoch die Habitatqualität und damit die Inanspruchnahme der Bestände durch Wildtiere. Für die nachhaltige Bewirtschaftung der natürlichen Ressourcen ist es notwendig, die Auswirkungen waldwirtschaftlicher Maßnahmen, insbesondere solcher zur Waldsanierung, auf die Habitatqualität zu verstehen und prognostizieren zu können. In Österreich sind Habitat-Qualitätsindices für Rehwild von Reimoser und Zandl (1994) entwickelt worden. Diese Indices beschreiben – für einen bestimmten Zeitpunkt – die Verwendbarkeit des Habitats für Rehwild. Eine Fragestellung bei der Waldsanierung ist die Einschätzung künftiger Habitatqualitäten unter unterschiedlichen Sanierungsstrategien. Für Bestände, die Bäume über einer vorgegebenen Kluppschwelle enthalten, kann der Zustand dieses Teils der Baumschicht mit Hilfe von Waldwachstumsmodellen prognostiziert werden. Diese Information genügt aber nicht, um die künftige Habitatqualität für Wildtiere abschätzen zu können. Im Rahmen dieser Arbeit sollten daher empirische Vegetationsmodelle entwickelt werden, mit deren Hilfe auch die Änderung der bodennahen Waldvegetation über der Zeit dargestellt werden kann. Die hier modellierten Vegetationstypen sind jene, die zur Berechnung der Habitatqualitätsindices für Rehwild notwendig sind.

Mit den Daten der Österreichischen Waldinventur wurde ein Modellansatz gewählt, der hierarchisch zwei Modelle aneinander koppelt. Zunächst wird mittels logistischer Regressionsmodelle die Wahrscheinlichkeit dafür, dass ein bestimmter Vegetationstyp nach einer vorgegebenen Periode vorhanden ist, modelliert. Anschließend wird für den Fall, dass der Vegetationstyp vorhanden ist, seine Flächendeckung mittels logarithmischer Regression quantifiziert. Im Laufe des Parametrisierens der Modelle wurden einige technische Aspekte bezüglich des verwendeten Datenmaterials untersucht. Dabei ergab sich, dass für die Quantifizierungsmodelle die Verwendung nur jener Probeflächen, auf denen der entsprechende Vegetationstyp vorhanden war, zu besseren Modellen im Sinne der Restvarianz und systematischer Abweichungen von den Beobachtungen führte. Für die logistischen Modelle war es notwendig, einen Schwellenwert der vorhergesagten Wahrscheinlichkeit zu finden, ab der die Entscheidung getroffen wird, dass der Vegetationstyp vorhanden ist. Als günstigster Schwellenwert ergab sich jener, der in der *a priori* Wahrscheinlichkeit für das Auftreten des Vegetationstyps resultierte. Dieser Modellansatz ist insofern neu, als 1) die Vegetationsentwicklung über der Zeit mittels eines dynamischen Modells beschrieben wird, 2) unabhängige Variable, die den Waldzustand zu Beginn und am Ende der Zuwachsperiode beschreiben, verwendet werden, wobei letztere mittels eines vorhandenen Waldwachstumssimulators prognostiziert werden. Insgesamt wurden 26 logistische und 25 logarithmische Modelle parametrisiert. Dabei wurde gefunden, dass der Vegetationszustand zu Beginn des Prognosezeitraums einen hohen Prognosewert für den künftigen Vegetationszustand hatte. Darüber hinaus waren Änderungen in der Baumschicht (über der Kluppschwelle), wie z.B. der Grundflächendichte und des Mitteldurchmessers auch von großer Bedeutung für die Güte der Prognose.

Nimmt man an, dass Eingriffe in die Baumschicht ein wichtiger Teil von Sanierungsmaßnahmen sind, dann kann man daraus schließen, dass Waldsanierungsmaßnahmen einen großen Einfluss auf die bodennahe Waldvegetation und damit auch auf die Habitatqualität für Rehwild haben. In der Anwendung können die hier entwickelten Modelle gemeinsam mit einem Waldwachstumssimulator dazu dienen, verschiedene forstwirtschaftliche Maßnahmen in ihrer Auswirkung auf die bodennahe Waldvegetation und die künftige Habitatqualität zu evaluieren.

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10 APPENDIX A

Table A - 1: The plot descriptors, by plot descriptor class, and their associated variable names used during modelling.

Tabelle A - 1: Die Flächenmerkmale der Österreichischen Waldinventur und ihre Variablen-bezeichnungen.

Plot Descriptor Class	**Plot Descriptor**	**Variable Name**	
		Logistic (0,1)	**Logarithmic (%)**
Growth Class	Regen I	*JUNGI T2*	*JUNGISH T2*
	Regen II	*JUNGII T2*	*JUNGIISH T2*
	Regen II – broadleaved	*N/A*	*BL JUNGIISH T2*
	Regen II – larch	*N/A*	*LA JUNGIISH T2*
Browse Class	No Browse	*A NO T2*	*A NOSH T2*
	Conifer Browse	*A ND T2*	*A NDSH T2*
	Deciduous Browse	*A LA T2*	*A LASH T2*
	Shrub Browse	*A ST T2*	*A STSH T2*
	Raspberry Browse	*A HI T2*	*A HISH T2*
	Blueberry Browse	*A HE T2*	*A HESH T2*
	Erica Browse	*A ER T2*	*A ERSH_T2*
	Herb Browse	*A KR T2*	*A KRSH_T2*
	Fern Browse	*A FA T2*	*A FASH_T2*
	Grass Browse	*A GR T2*	*A GRSH_T2*

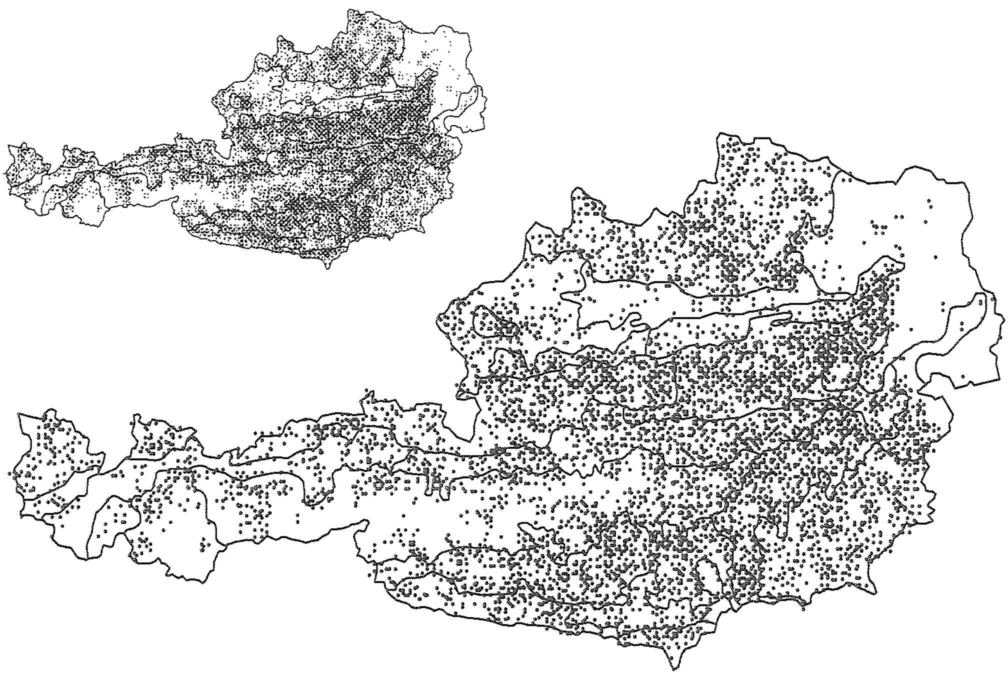

Figure A - 1: The distribution of the subplots within the No Browse class (large image) compared to the distribution of all the subplots used in model development (small image).

Abbildung A - 1: Verteilung aller Probeflächen ohne Äsung (großes Bild) im Vergleich zur Verteilung aller Probeflächen, die zur Modellerstellung verwendet wurden (kleines Bild).

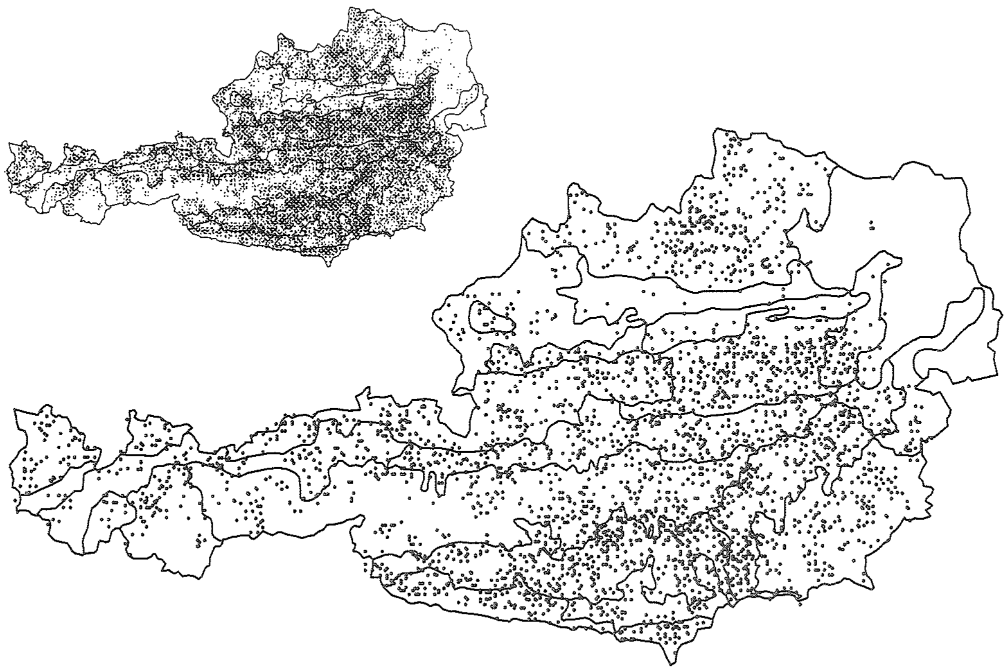

Figure A - 2: The distribution of the subplots within the Conifer Browse class (large image) compared to the distribution of all the subplots used in model development (small image).

Abbildung A - 2: Verteilung aller Probeflächen mit Nadelbaumäsung (großes Bild) im Vergleich zur Verteilung aller Probeflächen, die zur Modellerstellung verwendet wurden (kleines Bild).

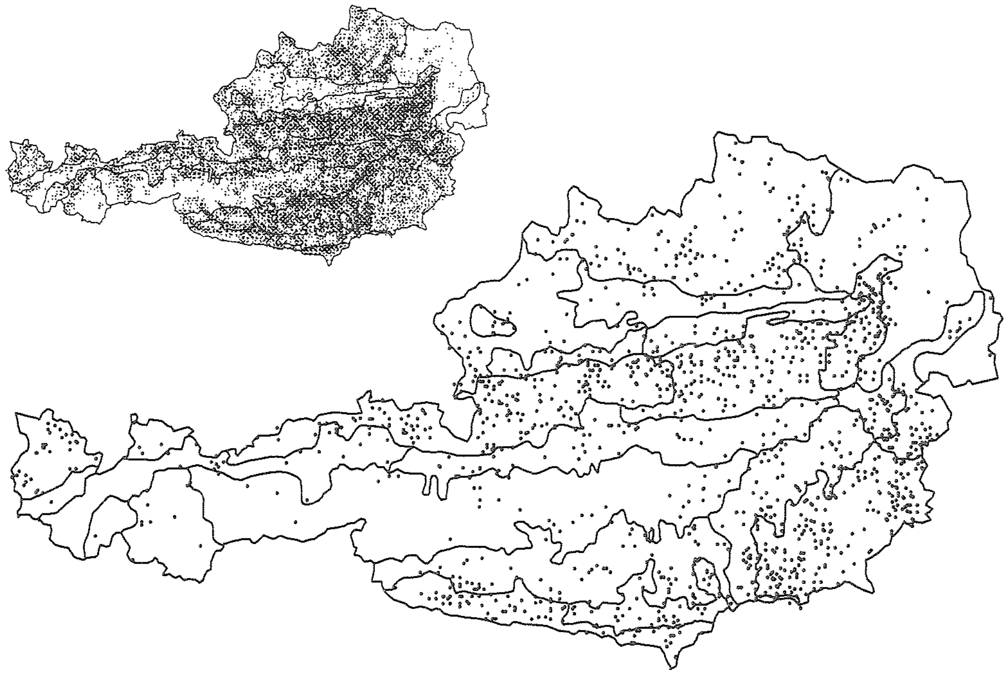

Figure A - 3: The distribution of the subplots within the Deciduous Browse class (large image) compared to the distribution of all the subplots used in model development (small image).

Abbildung A - 3: Verteilung aller Probeflächen mit Laubbaumäsung (großes Bild) im Vergleich zur Verteilung aller Probeflächen, die zur Modellerstellung verwendet wurden (kleines Bild).

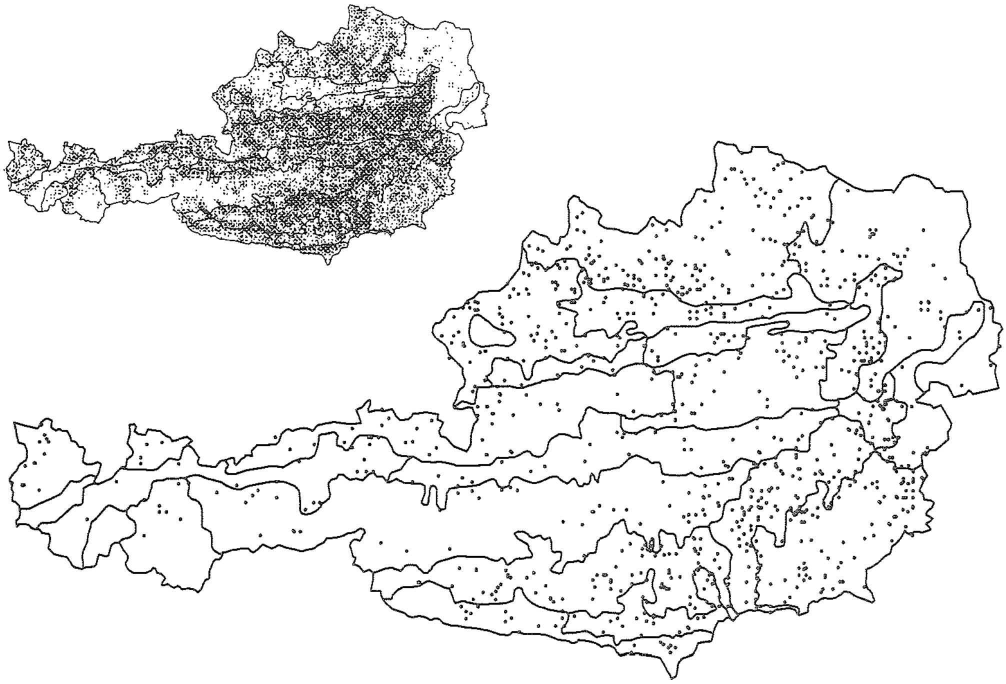

Figure A - 4: The distribution of the subplots within the Shrub Browse class (large image) compared to the distribution of all the subplots used in model development (small image).

Abbildung A - 4: Verteilung aller Probeflächen mit Sträuchern (großes Bild) im Vergleich zur Verteilung aller Probeflächen, die zur Modellerstellung verwendet wurden (kleines Bild).

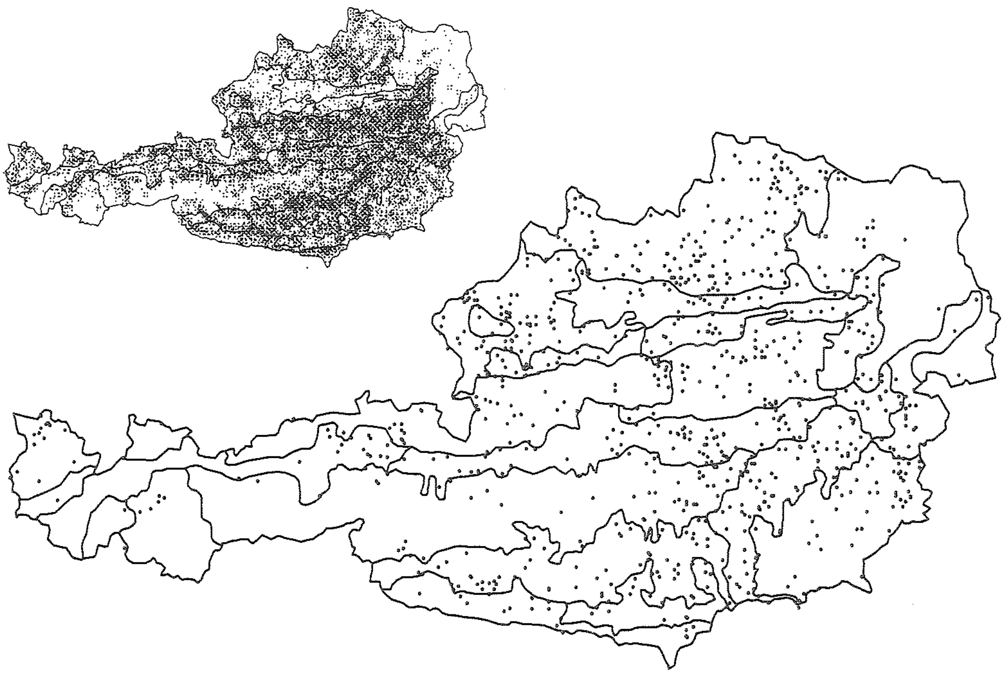

Figure A - 5: The distribution of the subplots within the Raspberry Browse class (large image) compared to the distribution of all the subplots used in model development (small image).

Abbildung A - 5: Verteilung aller Probeflächen mit Himbeere (großes Bild) im Vergleich zur Verteilung aller Probeflächen, die zur Modellerstellung verwendet wurden (kleines Bild).

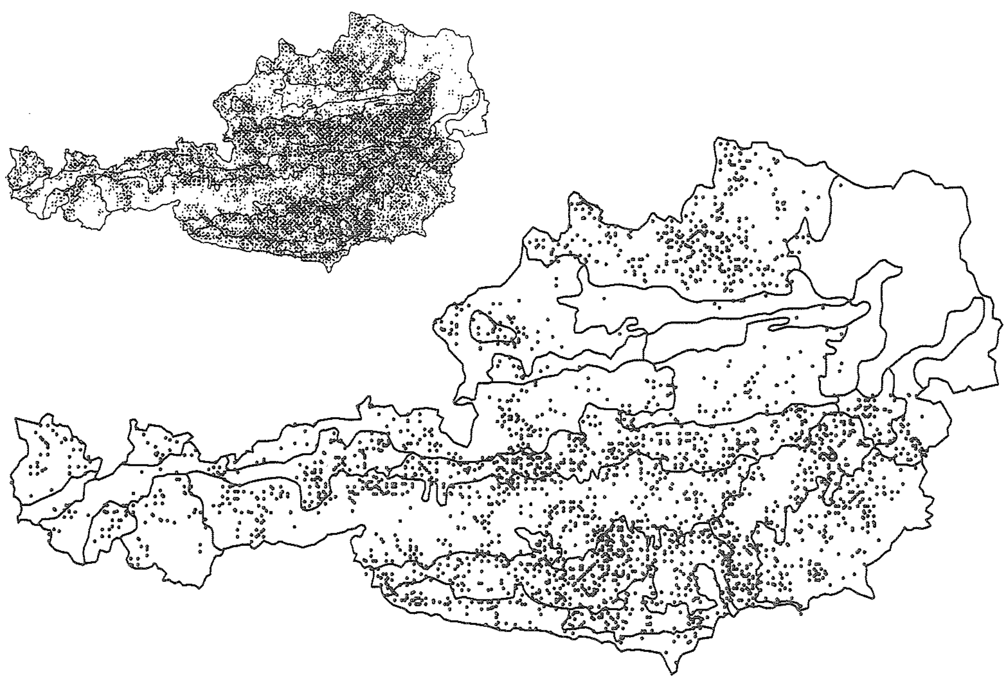

Figure A- 6: The distribution of the subplots within the Blueberry Browse class (large image) compared to the distribution of all the subplots used in model development (small image).

Abbildung A - 6: Verteilung aller Probeflächen mit Heidelbeere (großes Bild) im Vergleich zur Verteilung aller Probeflächen, die zur Modellerstellung verwendet wurden (kleines Bild).

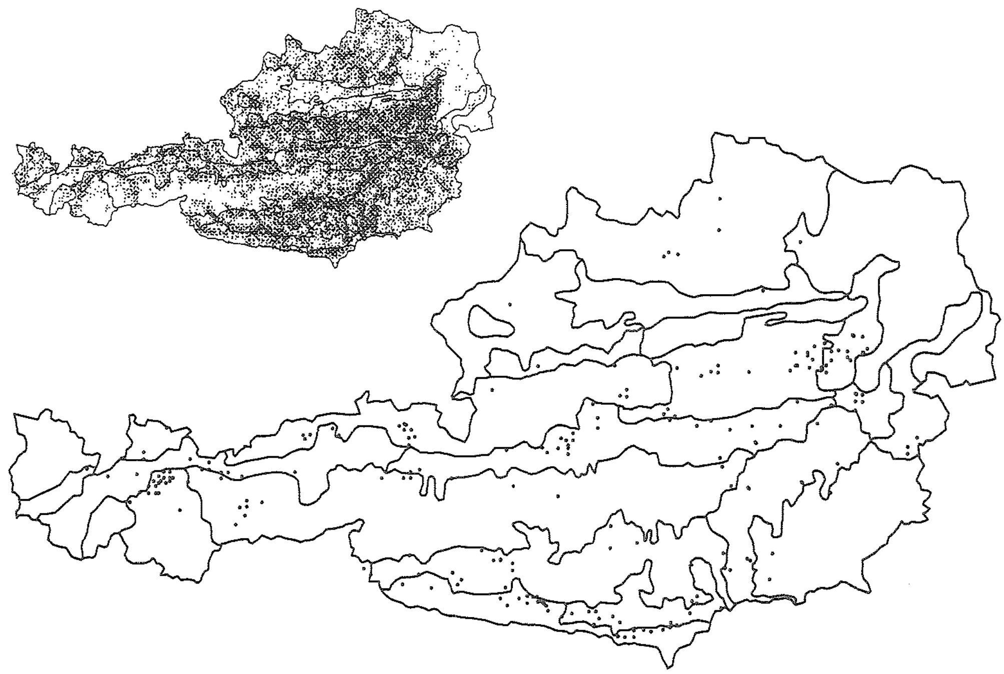

Figure A - 7: The distribution of the subplots within the Erica Browse class (large image) compared to the distribution of all the subplots used in model development (small image).

Abbildung A - 7: Verteilung aller Probeflächen mit Erika (großes Bild) im Vergleich zur Verteilung aller Probeflächen, die zur Modellerstellung verwendet wurden (kleines Bild).

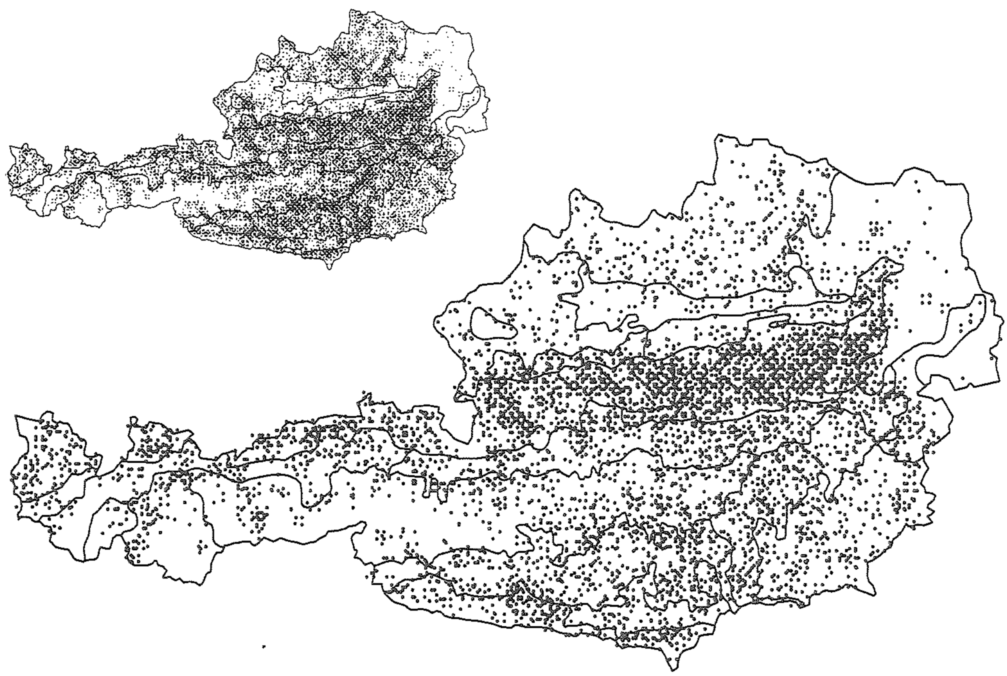

Figure A - 8: The distribution of the subplots within the Herb Browse class (large image) compared to the distribution of all the subplots used in model development (small image).

Abbildung A - 8: Verteilung aller Probeflächen mit Kräutern (großes Bild) im Vergleich zur Verteilung aller Probeflächen, die zur Modellerstellung verwendet wurden (kleines Bild).

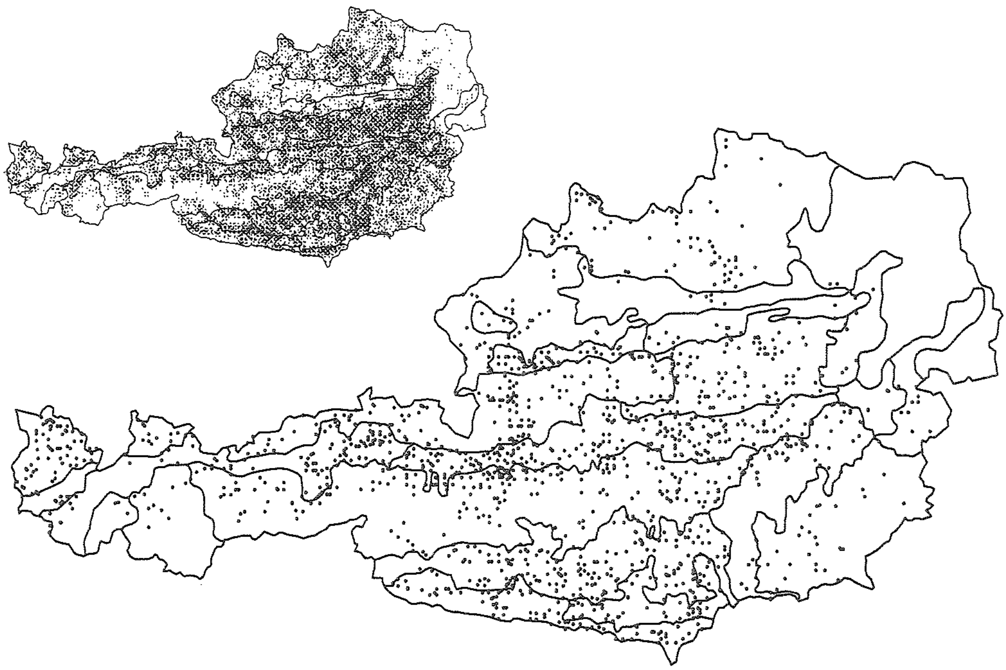

Figure A - 9: The distribution of the subplots within the Fern Browse class (large image) compared to the distribution of all the subplots used in model development (small image).

Abbildung A - 9: Verteilung aller Probeflächen mit Farnen (großes Bild) im Vergleich zur Verteilung aller Probeflächen, die zur Modellerstellung verwendet wurden (kleines Bild).

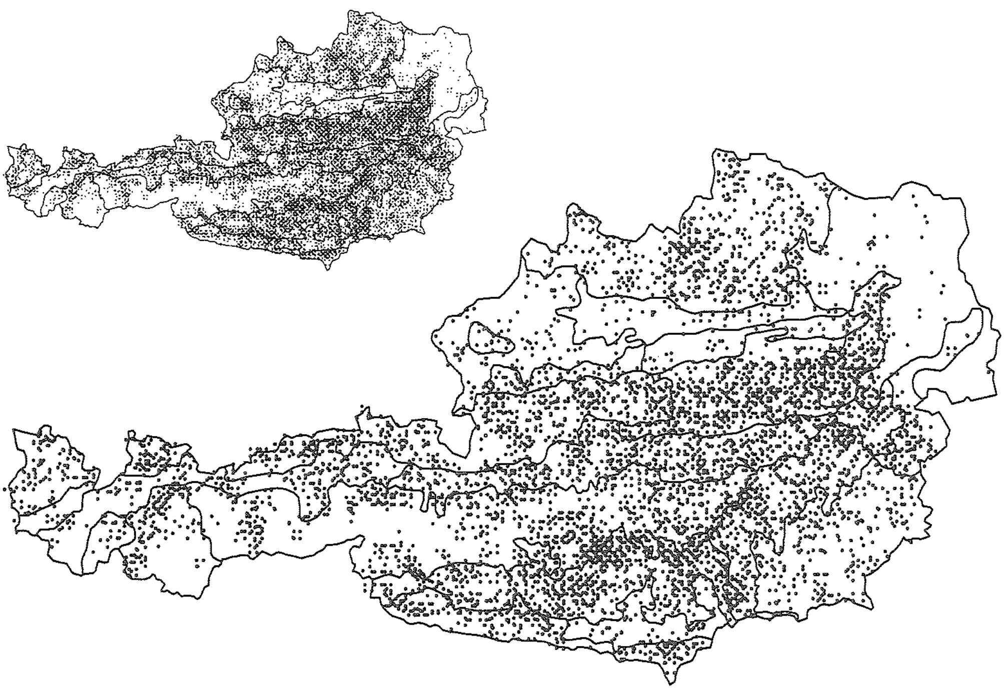

Figure A - 10: The distribution of the subplots within the Grass Browse class (large image) compared to the distribution of all the subplots used in model development (small image).

Abbildung A - 10: Verteilung aller Probeflächen mit Gräsern (großes Bild) im Vergleich zur Verteilung aller Probeflächen, die zur Modellerstellung verwendet wurden (kleines Bild).

Table A - 2: The ANFI Growth Class names, their inventory code, modelling variable name for both time 1 and time 2, a short description and the number of subplots represented by each growth class.

Tabelle A - 2: Die Wuchsklassen der Österreichischen Waldinventur, ihre Variablenbezeichnungen zu den Zeitpunkten t1 und t2, und die Anzahl der Probepunkte pro Wuchsklasse.

Code	Variable Name Time 2	Variable Name Time 1	Growth Class Name	Description	No. Subplots – Time 1
20	*JUNGISH_T1*	*JUNGISH_T2*	REGEN I	Regeneration to 1.3m height	1211
N/A	*BL_JUNGISH_T1*	*BL_JUNGISH_T2*	REGEN I – BROADLEAVED	Broadleaved Regeneration from 1.3m to 10.4cm DBH	N/A
N/A	*LA_JUNGISH_T1*	*LA_JUNGISH_T2*	REGEN I – LARCH	Larch Regeneration from 1.3m to 10.4cm DBH	N/A
30	*JUNGIISH_T1*	*JUNGIISH_T2*	REGEN II	Regeneration from 1.3m to 10.4cm DBH	8653
N/A	*BL_JUNGIISH_T1*	*BL_JUNGIISH_T2*	REGEN II – BROADLEAVED	Broadleaved Regeneration from 1.3m to 10.4cm DBH	N/A
N/A	*LA_JUNGIISH_T1*	*LA_JUNGIISH_T2*	REGEN II – LARCH	Larch Regeneration from 1.3m to 10.4cm DBH	N/A
40	*STANGSH_T1*	*STANGSH_T2*	POLE	Trees 10.5 to 20.4cm DBH	8673
50	*BHISH_T1*	*BHISH_T2*	MATURE I	Trees 20.5 to 35.4cm DBH	8525
60	*BHIISH_T1*	*BHIISH_T2*	MATURE II	Trees 35.5 to 50.4cm DBH	2840
70	*STARKSH_T1*	*STARKSH_T2*	OLD GROWTH	Trees greater than 50.5cm DBH	330

Table A - 3: The ANFI Wildlife Browse Class names, their inventory code, modelling variable name for both time 1 and time 2 and the number of subplots represented by each wildlife browse class.

Tabelle A - 3: Die Wildäsungstypen der Österreichischen Waldinventur, ihre Variablenbezeichnungen zu den Zeitpunkten t1 und t2 und die Anzahl der Probepunkte pro Wildäsungstyp.

Code	Variable Name Time 1	Variable Name Time 2	Browse Class Name	No. Subplots – Time 1
0	*A_NOSH_T1*	*A_NOSH_T2*	NO BROWSE	12789
1	*A_NDSH_T1*	*A_NDSH_T2*	CONIFER BROWSE	6308
2	*A_LASH_T1*	*A_LASH_T2*	DECIDUOUS BROWSE	3045
3	*A_STSH_T1*	*A_STSH_T2*	SHRUB BROWSE	1897
4	*A_HISH_T1*	*A_HISH_T2*	RASPBERRY BROWSE	1806
5	*A_HESH_T1*	*A_HESH_T2*	BLUEBERRY BROWSE	5584
6	*A_ERSH_T1*	*A_ERSH_T2*	ERICA BROWSE	444
7	*A_KRSH_T1*	*A_KRSH_T2*	HERB BROWSE	10985
8	*A_FASH_T1*	*A_FASH_T2*	FERN BROWSE	2852
9	*A_GRSH_T1*	*A_GRSH_T2*	GRASS BROWSE	11028

Table A - 4: The species groups used in the analysis, their modelling variable name and the number of subplots represented by each species group. Where; Pure: > 80% of one species, mixed coniferous: coniferous component > 50%, mixed deciduous: deciduous component > 50%.

Tabelle A - 4: Die verwendeten Mischungstypen, ihr Variablenname und die Anzahl der Probepunkte pro Mischungstyp. Reinbestand: > 80% von einer Baumart, Nadelholzmischbestand: >50% Nadelholz, Laubholzmischbestand: >50% Laubholz.

Variable Name Time 1	Variable Name Time 2	Species Group	No. Subplots – Time 1
STD0_T1	*STD0_T2*	NO TREES IN ANGLE COUNT	3087
STD1_T1	*STD1_T2*	NORWAY SPRUCE (*PICEA ABIES*, L. KARST)	6393
STD2_T1	*STD2_T2*	WHITE FIR (*ABIES ALBA* MILL.)	162
STD3_T1	*STD3_T2*	EUROPEAN LARCH (*LARIX DECIDUA* MILL.)	364
STD4_T1	*STD4_T2*	SCOTS PINE (*PINUS SYLVESTRIS* L.)	591
STD5_T1	*STD5_T2*	BLACK PINE (*PINUS NIGRA* ARNOLD)	116
STD6_T1	*STD6_T2*	STONE PINE (*PINUS CEMBRA* L.)	60
STD10_T1	*STD10_T2*	BEECH (*FAGUS SILVATICA* L.)	608
STD11_T1	*STD11_T2*	OAK (*QUERCUS* SPP.)	142
STD40_T1	*STD40_T2*	MIXED CONIFEROUS	4584
STD41_T1	*STD41_T2*	MIXED DECIDUOUS	1969

Table A - 5: The ANFI aspect classes, their modelling variable name, inventory code and the number of subplots represented by each aspect class.

Tabelle A - 5: Die Exposition nach der Österreichischen Waldinventur, ihre Variablennamen und die Anzahl der Probepunkte pro Expositionsklasse.

Code	Variable Name	Aspect	No. Subplots – Time 1
0	*ASD0*	NO ASPECT	1478
1	*ASD1*	NORTH	2734
2	*ASD2*	NORTHEAST	2174
3	*ASD3*	EAST	2079
4	*ASD4*	SOUTHEAST	1554
5	*ASD5*	SOUTH	2322
6	*ASD6*	SOUTHWEST	1699
7	*ASD7*	WEST	2060
8	*ASD8*	NORTHWEST	1976

Table A - 6: The ANFI slope classes, their modelling variable name, inventory code and the number of subplots represented by each slope class.

Tabelle A - 6: Die Hangneigung nach der Österreichischen Waldinventur, ihre Variablennamen und die Anzahl der Probepunkte pro Hangneigungsklasse.

Code	Variable Name	Slope position	No. Subplots – Time 1
1	*RLD1*	CONVEX UPPER SLOPE	977
2	*RLD2*	MIDDLE SLOPE	14247
3	*RLD3*	CONCAVE LOWER SLOPE	978
4	*RLD4*	DITCH	101
5	*RLD5*	VALLEY BOTTOM	51
6	*RLD6*	PLAIN	1687
7	*RLD7*	HOLLOW	33

Table A - 7: The ANFI Vegetation types, their modelling variable name, inventory code and the number of subplots represented by each vegetation type, taken from Monserud and Sterba (1996).

Tabelle A - 7: Die Vegetationstypen der Österreichischen Waldinventur, ihre Variablennamen und die Anzahl der Probepunkte pro Vegetationstyp, nach Monserud und Sterba (1996).

Code	Variable name	Name	No. Subplots – Time 1
1	*GVD1*	SHADE-TOLERANT HERBS TYPES	2103
2	*GVD2*	MODERATELY MOIST HERB TYPES	1481
3	*GVD3*	THERMOPHILIC HERB TYPES	228
4	*GVD4*	*OXALIS ACETOSELLA* TYPES	4555
5	*GVD5*	LUXURIANT MOSS-*VACCINIUM-AVENELLA* TYPE	660
6	*GVD6*	SPARSE MOSS-*VACCINIUM-AVENELLA* TYPE	3929
7	*GVD7*	MOSS TYPE	98
8	*GVD8*	*AVENELLA* TYPE	158
9	*GVD9*	DRY BLUEBERRY-CRANBERRY TYPE	42
10	*GVD10*	*CALLUNA* TYPE	45
11	*GVD11*	SPHAGNUM-*VACCINIUM-AVENELLA* TYPE	98
12	*GVD12*	COMPETING GRASS COVER	2119
13	*GVD13*	DEPLETION OR LITTER EROSION SITES	52
14	*GVD14*	SUBALPINE DWARF SHRUBS	94
15	*GVD15*	*ERICA* TYPE	162
16	*GVD16*	PASTURE FOREST TYPES	396
17	*GVD17*	PIONEER VEGETATION	3
18	*GVD18*	SEEP VEGETATION TYPES	183
19	*GVD19*	HYDROPHYTIC PERENNIAL SHRUB TYPE	1582
20	*GVD20*	FLOODPLAIN OR ALLUVIAL FOREST TYPES	85

Table A - 8: The ANFI stand structure classes, their modelling variable name, inventory code and the number of subplots represented by each stand structure class.

Tabelle A - 8: Die Bestandesstruktur nach der Österreichischen Waldinventur, die Variablennamen und die Anzahl der Probepunkte pro Bestandesstrukturklasse.

Code	Variable Name Time 1	Variable Name Time 2	Structure Class	No. Subplots – Time 1
1	*SSD1_T1*	*SSD1_T2*	1 LAYER	13822
2	*SSD2_T1*	*SSD2_T2*	2 LAYER	3767
3	*SSD3_T1*	*SSD3_T2*	MULTILAYER	487

Table A- 9: ANFI Soil groups transcribed into the FAO-UNESCO (1989) soil groups, their modelling variable names, inventory code, and the number of subplots represented by each soil group, taken from Sterba and Monserud (1996).

Tabelle A - 9: Die Bodentypen der Österreichischen Waldinventur in ihrer Bezeichnung nach FAO-UNESCO (1989), ihre Variablenname und die Anzahl der Probepunkte pro Bodentyp, nach Monserud und Sterba (1996).

Code	Variable Name	Soil group	No. Subplots – Time 1
1	*SCD1*	Leptosols derived from noncalcareous material (Lithic Leptosols, Umbric Leptosols and Arenosols)	132
2	*SCD2*	Dystric Cambisols, Ferralic Cambisols and colluvial soils derived from dystric silicate material	1740
3	*SCD3*	Eutric Cambisols, colluvial soils derived from eutric silicate material and Calcareous Cambisols	1634
4	*SCD4*	Spodi-Dystric Cambisol on silicate material	4517
5	*SCD5*	Climate-induced Podzols derived from dystric silicate material	631
6	*SCD6*	Substrate-induced Podzols (derived form Quartzite, Quartz-Phyllite, Quartz-Sand, Quartz sandstone, Arkose)	349
7	*SCD7*	Substrate-induced Gleyic Podzol	66
8	*SCD8*	Light-textured Cambisols and Spodic Cambisols derived from unconsolidated sediments	516
9	*SCD9*	Heavy-textured Cambisols and Luvisols derived from moraine material, non-calcareous loess, or mudstone	443
10	*SCD10*	Cambisols and Luvisols derived from calcareous loess	203
11	*SCD11*	(Eutric) Planosols and Stagnic Gleysols derived from flysch or mudstone	633
12	*SCD12*	(Eutric) Planosols and Stagnic Gleysols derived from loess	81
13	*SCD13*	Temporarily waterlogged (Stagno-gleyic) soils on unconsolidated sediments	775
14	*SCD14*	Stagnic Cambisols or Gleysols with marked interflow	291
15	*SCD15*	Relic soil material showing ferralic properties (Ferralic Cambisols)	309
16	*SCD16*	Chernozems	10
17	*SCD17*	Leptosols derived from calcareous material (Rendzic Leptosols and Lithic Leptosols)	1918
18	*SCD18*	Colluvial soils showing properties of both Rendzic Leptosols and Chromic Cambisols (Terra Fusca)	1628
19	*SCD19*	Chromic Cambisols on calcareous bedrock (Terra Fusca)	1517
20	*SCD20*	Gleysols	145
21	*SCD21*	Fluvisols along small rivers	149
22	*SCD22*	Fluvisols	134
23	*SCD23*	Mollic and Umbric Gleysols	171
24	*SCD24*	Histic Gleysols and Terric Histosols	7
25	*SCD25*	Fibric Histosols	24
26	*SCD26*	Anthrosols	53

Table A - 10: The ANFI growth districts, their modelling variable names, inventory code and the number of subplots represented by each growth district, taken from Monserud and Sterba (1996).

Tabelle A - 10: Die Wuchsbezirke nach der Österreichischen Waldinventur, ihre Variablennamen und die Anzahl der Probepunkte pro Wuchsbezirk nach Monserud und Sterba (1996).

Code	Variable Name	Growth District	No. Subplots – Time 1
1	*GZD1*	AUSTRIAN PART OF THE BOHEMIAN MASSIF	1966
2	*GZD2*	EASTERN PANNONIC SEMIARID REGION	259
3	*GZD3*	HILLS AND PLAINS BETWEEN THE ALPS AND THE DANUBE, EASTERN PART	223
4 or 5	*GZD4,5*	HILLS AND PLAINS BETWEEN THE DANUBE, WESTERN PART AND KOBERNAUSSERWALD	527
6	*GZD6*	EASTERN EDGE OF THE ALPS	532
7	*GZD7*	EASTERN FLYSCH ALPS	41
8	*GZD8*	WESTERN FLYSCHALPS WITH HUMID CLIMATE	543
9	*GZD9*	NORTHERN CALCAREOUS ALPS, EASTERN PART	1682
10	*GZD10*	NORTHERN CALCAREOUS ALPS, WESTERN PART	1839
11	*GZD11*	NORTHERN CENTRAL ALPS, EASTERN PART	1373
12	*GZD12*	NORTHERN CENTRAL ALPS, WESTERN PART	617
13	*GZD13*	CENTRAL ALPS	2085
14	*GZD14*	INNER CENTRAL ALPS WITH CONTINENTAL CLIMATE	285
15	*GZD15*	SOUTHERN CENTRAL ALPS	1820
16	*GZD16*	KLAGENFURT VALLEY	288
17	*GZD17*	AUSTRIAN SOUTHERN ALPS	750
18	*GZD18*	SOUTH-EASTERN EDGE OF THE AUSTRIAN ALPS	1225
19	*GZD19*	GRANITE HILLS ON THE EASTERN EDGE OF THE ALPS	351
20	*GZD20*	SOUTH-EASTERN HILLS AND TERRACES	1065
21	*GZD21*	MOUNTAINS OF THE MIDDLE „BURGENLAND“	254

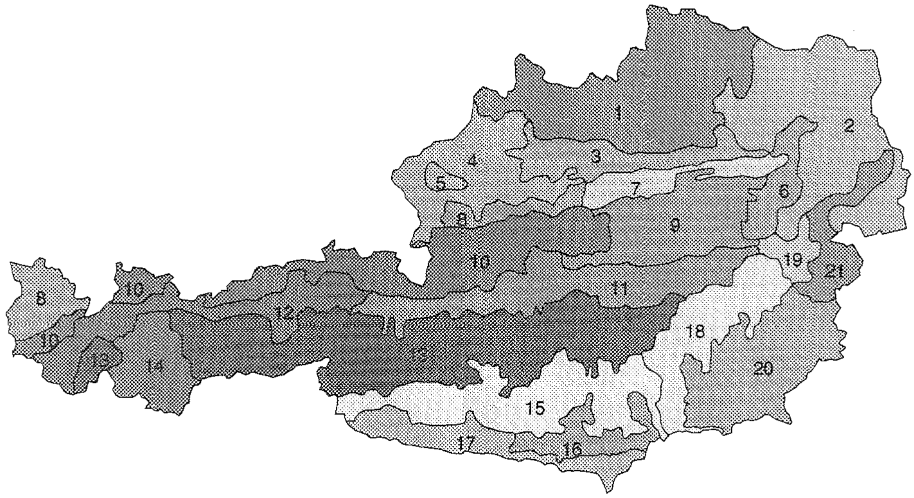

Figure A - 11: Growth Zones of Austria.
Abbildung A - 11: Wuchsbezirke Österreichs.

11 APPENDIX B

Table B - 1: Logistic regression for Regen I – 1 (with trees). Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 1: Logistische Regression für Verjüngung I „REGEN I" – 1 (Probeflächen mit Bäumen in der Winkelzählprobe). Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > Chi-Square
INTERCEPT	Intercept	-0.1162	0.3979	0.7703
LN(A_NOSH_T1)	No Browse	0.6158	0.1917	0.0013
A_GRSH_T1	Grass Browse	0.2038	0.0624	0.0011
GZD10	Growth Zone 10	0.8584	0.3683	0.0198
GZD7	Growth Zone 7	2.0060	1.1560	0.0827
GZD19,20	Growth Zone 19, 20	-1.7917	0.8034	0.0257
GVD2	Moist Herb Type	1.5429	0.4953	0.0018
SSD1_T2	1 Layer Stand	-1.1512	0.2693	<.0001
C_QMD	Change in Quadratic Mean Diameter	0.0349	0.0204	0.0870
ASD7	West Aspect	0.5593	0.3149	0.0757
STANGSH_T2	Pole Stand	-0.3660	0.1108	0.0010

Hosmer-Lemeshow statistic = 11.4682 with 8 DF (p=0.1766)
ROC = .76
A Priori Probability = .48, Threshold Probability = .49
n = 382

Table B - 2: Logistic regression for Regen I - 1 (no trees). Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 2: Logistische Regression für Verjüngung I „REGEN I" – 1 (Probeflächen ohne Bäume in der Winkelzählprobe). Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die a priori Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > Chi-Square
INTERCEPT	Intercept	0.2185	0.9118	0.8106
ELEV	Elevation	0.2145	0.0243	<.0001
INTVAL	Interval Length	-0.5913	0.1685	0.0004
STD1_T2	Norway Spruce	-1.6164	0.3959	<.0001
GZD9,10,12	Growth Zone 9, 10 or 12	0.8463	0.1775	<.0001
RLD3,4,7	Concave Lower Slope, Ditch or Hollow	-2.0624	0.7508	0.0060
LN(A_NOSH_T1)	No Browse	0.5530	0.1523	0.0003

Hosmer-Lemeshow statistic = 10.0366 with 8 DF (p=0.2625)
ROC = .77
A Priori Probability = .37, Threshold Probability = .46
n = 801

Table B - 3: Logistic regression for Regen II - 1 (with trees). Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 3: Logistische Regression für Verjüngung II „REGEN II" – 1 (Probeflächen mit Bäumen in der Winkelzählprobe). Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	1.0628	0.5513	0.0539
LN(JUNGIISH_T1)	Regen II	1.9059	0.2276	<.0001
SSD1_T2 X LN(JUNGIISH_T1)	Regen II x 1 layer stand	-1.7623	0.2350	<.0001
SSD1_T2	1 layer stand	1.0625	0.2988	0.0004
STD1_T2	Norway Spruce	-0.9349	0.0911	<.0001
C_QMD	Change in Quadratic Mean Diameter	-0.0943	0.0108	<.0001
ELEV	Elevation	0.0586	0.0117	<.0001
A_NDSH_T1	Conifer Browse	0.2580	0.0366	<.0001
INTVAL	Interval Value	-0.1762	0.0834	0.0346

Hosmer-Lemeshow statistic = 8.2781 with 8 DF (p=0.4068)
ROC = .76
A Priori Probability = .89, Threshold Probability = .77
n = 6713

Table B - 4: Logistic regression for Regen II - 1 (no trees). Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 4: Logistische Regression für Verjüngung II „REGEN II" – 1 (Probeflächen ohne Bäume in der Winkelzählprobe). Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die a priori Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	1.3796	0.5691	0.0153
ELEV	Elevation	0.1165	0.0321	0.0003
SSD1_T2	1 Layer Stand	-1.4156	0.4814	0.0033
A_LASH_T1	Deciduous Browse	0.3628	0.1191	0.0023
A_NDSH_T1	Conifer Browse	0.2294	0.0737	0.0018
JUNGIISH_T1	Regen II	0.0878	0.0362	0.0152

Hosmer-Lemeshow statistic =7.8098 with 8 DF (p=0.4523)
ROC = .72
A Priori Probability = .95, Threshold Probability = .87
n = 1781

Table B - 5: Logistic regression for Regen II - 0 (with trees). Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 5: Logistische Regression für Verjüngung II „REGEN II" – 0 (Probeflächen mit Bäumen in der Winkelzählprobe). Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	-0.3695	0.1564	0.0181
ELEV	Elevation	-0.1016	0.0123	<.0001
A_NOSH_T1	No Browse	-0.1659	0.0154	<.0001
STD0_T2	No trees in angle count	1.2079	0.2046	<.0001
GZD7,9,10	Growth Zone 7, 9 or 10	-0.4618	0.1254	0.0002
SCD3,4	Soil Group 3 or 4	0.3663	0.1102	0.0009
RLD3	Concave Lower Slope	0.4787	0.1842	0.0093
SSD1_T2	1 Layer Stand	-1.2953	0.1059	<.0001
JUNGISH_T1	Regen I	0.2903	0.0175	<.0001

Hosmer-Lemeshow statistic =3.0400 with 8 DF (p=0.9318)
ROC = .79
A Priori Probability = .08, Threshold Probability = .18
n = 8121

Table B - 6: Logistic regression for Regen II - 0 (no trees). Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 6: Logistische Regression für Verjüngung II „REGEN II" – 0 (Probeflächen ohne Bäume in der Winkelzählprobe). Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die a priori Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	-3.3376	0.8776	0.0001
ELEV	Elevation	-0.1724	0.0220	<.0001
JUNGISH_T1	Regen I	0.3373	0.0263	<.0001
A_NOSH_T1	No Browse	-0.1896	0.0416	<.0001
INTVAL	Interval Value	0.4732	0.1516	0.0018
RLD3,7	Concave Lower Slope or Hollow	1.0282	0.3788	0.0066
GZD6	Growth Zone 6	-1.2731	0.4883	0.0091
GZD9,10,12	Growth Zone 9, 10 or 12	-0.8204	0.1686	<.0001

Hosmer-Lemeshow statistic = 12.5077 with 8 DF (p=0.1299)
ROC =.85
A Priori Probability = .48, Threshold Probability = .56
n = 1130

Table B - 7: Logistic regression for No Browse – 1. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 7: Logistische Regression für Keine Äsung – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	7.9284	0.3639	<.0001
C_BA	Change in Basal Area	0.0176	0.00272	<.0001
INTVAL	Interval Value	-1.5114	0.0634	<.0001
STD0_T2	No Trees in Angle Count	-1.1637	0.0938	<.0001
JUNGIISH_T1	Regen II	0.1075	0.0103	<.0001
GVD6	Sparse Moss Type	0.3451	0.0699	<.0001
STANGSH_T2	Pole Stand	0.0694	0.0115	<.0001
SSD1_T2	1 Layer Stand	-0.1897	0.0697	0.0065
CCF_T2	Crown Competition Factor	0.000589	0.000137	<.0001
STD41_T2	Mixed Deciduous	-0.4850	0.0973	<.0001
A_NOSH_T1	No Browse	0.3800	0.0128	<.0001

Hosmer-Lemeshow statistic =5.6990 with 8 DF (p=0.6809)
ROC = .83
A Priori Probability = .86, Threshold Probability = .68
n = 12779

Table B - 8: Logistic regression for No Browse – 0. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 8: Logistische Regression für Keine Äsung – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	-3.7595	0.3917	<.0001
ELEV	Elevation	-0.0487	0.00835	<.0001
INTVAL	Interval Value	0.3489	0.0647	<.0001
STD0_T2	No Trees in Angle Count	-0.2576	0.0945	0.0064
STD1_T2	Norway Spruce	0.3126	0.0769	<.0001
GZD9	Growth Zone 9	-0.3341	0.1157	0.0039
GVD1,2,4,6	Shade Herb, Moist Herb, Moderhumus or Sparse Moss Types	0.5799	0.0703	<.0001
C_BA	Change in Basal Area	0.0181	0.00404	<.0001
SCD3	Soil Group 3	0.3240	0.1023	0.0015
JUNGIISH_T1	Regen II	0.1161	0.00983	<.0001
[5]*OVERSH_T2*^{2}	Sum of Overstory Classes	0.00924	0.000935	<.0001
GZD15,18	Growth Zone 15, 18	0.4167	0.0880	<.0001
A_GRSH_T1	Grass Browse	-0.0435	0.0153	0.0044
[6]*ASUNGSH_T1*^{2}	Sum of Browse Classes	0.0168	0.00186	<.0001

Hosmer-Lemeshow statistic = 12.9188 with 8 DF (p=0.1147)
ROC = .73
A Priori Probability = .32, Threshold Probability = .39
n = 5280

[5] OVERSH_T2 = STANGSH_T2 + BHISH_T2 + BHIISH_T2
[6] ASUNGSH_T1 = A_NDSH_T1 + A_LASH_T1 + A_STSH_T1

Table B - 9: Logistic regression for Deciduous Browse – 1. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 9: Logistische Regression für Laubbäume – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	2.6354	0.5085	<.0001
ELEV	Elevation	-0.0462	0.0144	0.0013
INTVAL	Interval Value	-0.4624	0.0833	<.0001
GZD9,10	Growth Zone 9 or 10	0.5513	0.1085	<.0001
SCD11	Soil Group 11	0.7188	0.1909	0.0002
RLD1	Convex Upper Slope	0.5177	0.1840	0.0049
GVD4	Moderhumus in Conifer Stands	-0.1340	0.1163	0.2491
C_BA	Change in Basal Area	-0.0175	0.00419	<.0001
LN(A_LASH_T1)	Deciduous Browse	1.2491	0.1340	<.0001
A_NOSH_T1	No Browse	-0.1120	0.0172	<.0001
STD1_T2	Norway Spruce	-0.1885	0.1068	0.0776

Hosmer-Lemeshow statistic = 6.4478 with 8 DF (p= 0.5972)
ROC = .70
A Priori Probability = .68, Threshold Probability = .61
n = 3036

Table B - 10: Logistic regression for Deciduous Browse – 0. Presented in th e table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 10: Logistische Regression für Laubbäume – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	-5.7788	0.3499	<.0001
ELEV	Elevation	0.1313	0.0386	0.0007
ELEV²		-0.0192	0.00238	<.0001
INTVAL	Interval Value	0.8028	0.0570	<.0001
STD1_T2	Norway Spruce	-0.5156	0.0697	<.0001
STD10,41	Beech or Mixed Deciduous	0.4346	0.0742	<.0001
GVD1,3,19	Shade Herb, Thermophilic Herb or Hydrophytic Shrub	0.7077	0.0720	<.0001
GVD2,4	Moist Herb or Moderhumus in Conifer Stands	0.3756	0.0727	<.0001
C_BA	Change in Basal Area	-0.0126	0.00245	<.0001
GZD8,10	Growth Zone 8 or 10	0.3230	0.0777	<.0001
GZD1	Growth Zone 1	-0.3341	0.0930	0.0003
GZD4	Growth Zone 4	-0.6277	0.1601	<.0001
LN(A_NOSH_T1)	No Browse	-0.4389	0.0336	<.0001

Hosmer-Lemeshow statistic = 3.3892 with 8 DF (p= 0.9076)
ROC = .78
A Priori Probability = .11, Threshold Probability = .25
n = 15023

Table B - 11: Logistic regression for Shrub Browse – 1. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 11: Logistische Regression für Sträucher – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	2.8397	0.6235	<.0001
ELEV	Elevation	-0.0833	0.0204	<.0001
SLPE	Slope	0.0653	0.0209	0.0018
INTVAL	Interval Value	-0.5097	0.1018	<.0001
SCD4	Soil Group 4	-0.4953	0.1582	0.0017
JUNGIISH_T1	Regen II	-0.0587	0.0133	<.0001
GVD4,19	Moderhumus in Conifer Stands	-0.3366	0.1041	0.0012
GZD20	Growth Zone 20	-0.6952	0.1993	0.0005
A_NOSH_T1	No Browse	-0.0650	0.0221	0.0032
A_STSH_T1	Shrub Browse	0.4883	0.0529	<.0001

Hosmer-Lemeshow statistic =5.9022 with 8 DF (p=0.6582)
ROC = .71
A Priori Probability =.62, Threshold Probability = .57
n = 1889

Table B - 12: Logistic regression for Shrub Browse – 0. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 12: Logistische Regression für Sträucher – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	-4.2330	0.4412	<.0001
ELEV	Elevation	-0.2228	0.0169	<.0001
A_NOSH_T1	No Browse	-0.1299	0.0117	<.0001
INTVAL	Interval Value	0.6450	0.0754	<.0001
GZD13	Growth Zone 13	3.0132	0.5091	<.0001
ELEV X GZ13	Elevation x Growth Zone 13	-0.1971	0.0478	<.0001
ASD4,6	Southeast or Southwest Aspect	0.4484	0.0894	<.0001
SSD1_T2	1 Layer Stand	-0.2691	0.0825	0.0011
GVD1,19	Shade Herb or Hydrophytic Shrub	0.6547	0.0811	<.0001
GVD6,7	Sparse Moss or Moss Type	-0.7501	0.1210	<.0001
GVD14	Subalpine Dwarf Shrub Type	2.8100	0.4799	<.0001
C_BA	Change in Basal Area	-0.0105	0.00325	0.0013
[7]*GRP_GZ*	Group of Growth Zones	1.5984	0.2500	<.0001
ELEV X GRP_GZ	Elevation x Group of Growth Zones	-0.1405	0.0310	<.0001
STD10_T2	Beech	-1.0597	0.2607	<.0001

Hosmer-Lemeshow statistic = 14.2304 with 8 DF (p=0.0760)
ROC = .80
A Priori Probability = .05, Threshold Probability = .18
n = 16170

[7] GRP_GZ = GZD11 OR GZD12 OR GZD15 OR GZD17 OR GZD18

Table B - 13: Logistic regression for Raspberry Browse – 1. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 13: Logistische Regression für Himbeere – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	3.2534	0.6514	<.0001
ELEV	Elevation	-0.0652	0.0167	<.0001
JUNGIISH_T1	Regen II	-0.0888	0.0131	<.0001
STD1_T2	Norway Spruce	-0.2932	0.1191	0.0138
INTVAL	Interval Value	-0.6067	0.1091	<.0001
SCD17,22	Soil Group 17 or 22	-0.7428	0.2410	0.0021
GVD4,19	Moderhumus in Conifer stands or Hydrophytic Shrub Types	0.7765	0.1174	<.0001
A_NOSH_T1	No Browse	-0.0871	0.0270	0.0013
A_HISH_T1	Raspberry Browse	0.4041	0.0470	<.0001

Hosmer-Lemeshow statistic =13.0283 with 8 DF (p=0.1109)
ROC = .75
A Priori Probability = .63, Threshold Probability = .56
n = 1803

Table B - 14: Logistic regression for Raspberry Browse - 0. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 14: Logistische Regression für Himbeere – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	-5.0943	0.4217	<.0001
ELEV	Elevation	-0.1017	0.00933	<.0001
STD0_T2	No Trees in Angle Count	0.6807	0.0904	<.0001
C_BA	Change in Basal Area	-0.0196	0.00273	<.0001
C_BA^2		0.000234	0.000043	<.0001
INTVAL	Interval Value	0.5670	0.0731	<.0001
SCD17,18,20,21	Soil Group 17, 18, 20 and 21	-1.1025	0.1167	<.0001
SCD19	Soil Group 19	-0.5126	0.1413	0.0003
GVD19	Hydrophytic Shrub Type	1.7240	0.1111	<.0001
GVD1,4	Shade Herb or Moderhumus in Conifer Stands Types	0.6086	0.0818	<.0001
LN(A_NOSH_T1)	No Browse	-0.3145	0.0443	<.0001
GZD17	Growth Zone 17	-0.8046	0.2893	0.0054

Hosmer-Lemeshow statistic = 3.9777 with 8 DF (p=0.8591)
ROC = .76
A Priori Probability = .06, Threshold Probability = .15
n = 16254

Table B - 15: Logistic regression for Blueberry Browse – 1. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 15: Logistische Regression für Heidelbeere – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	3.0306	0.4794	<.0001
ELEV	Elevation	0.0806	0.0119	<.0001
INTVAL	Interval Value	-0.7028	0.0808	<.0001
SLPE	Slope	-0.0691	0.0190	0.0003
STD0_T2	No Trees in Angle Count	-0.4369	0.1208	0.0003
GZD17	Growth Zone 17	-0.5203	0.1920	0.0067
SCD2	Soil Group 2	-0.3211	0.1304	0.0138
GVD6	Sparse Moss	0.2984	0.1028	0.0037
GVD4	Moderhumus in Conifer Stands	-0.3936	0.1206	0.0011
GVD19	Hydrophytic Shrub Type	-0.7849	0.2127	0.0002
A_HESH_T1	Blueberry Browse	0.5826	0.0338	<.0001
C_BA	Change in Basal Area	0.0122	0.00360	0.0007

Hosmer-Lemeshow statistic = 13.0757 with 8 DF (p=0.1093)
ROC = .80
A Priori Probability = .84, Threshold Probability = .68
n = 5580

Table B - 16: Logistic regression for Blueberry Browse – 0. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 16: Logistische Regression für Heidelbeere – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	-5.8901	0.4475	<.0001
SCD2,4	Soil Group 2 or 4	0.5632	0.0831	<.0001
SCD5,6	Soil Group 5 or 6	1.1390	0.1741	<.0001
ASD2,8	Northeast or Northwest Aspect	0.4302	0.0846	<.0001
ELEV	Elevation	0.1513	0.0116	<.0001
STD41_T2	Mixed Deciduous	-0.7867	0.2094	0.0002
INTVAL	Interval Value	0.4109	0.0769	<.0001
SLPE	Slope	-0.1354	0.0180	<.0001
JUNGISH_T1^2	Regen II	-0.00523	0.00163	0.0013
CCF_T2	Crown Competition Factor	-0.00086	0.000220	<.0001
GVD6	Sparse Moss Type	1.5334	0.1100	<.0001

Hosmer-Lemeshow statistic = 15.8413 with 8 DF (p=0.0447)
ROC = .77
A Priori Probability =.07, Threshold Probability = .17
n = 12426

Table B - 17: Logistic regression for Erica Browse – 1. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 17: Logistische Regression für Erika – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	9.6116	1.4338	<.0001
WTRG	Water Regime	-0.8594	0.2098	<.0001
GZD1	Growth Zone 1	-2.0631	0.7105	0.0037
GVD15	Erica Type	1.3122	0.2870	<.0001
INTVAL	Interval Value	-1.3413	0.2337	<.0001

Hosmer-Lemeshow statistic = 6.0071 with 6 DF (p=0.4224)
ROC = .78
A Priori Probability = .64, Threshold Probability = .58
n = 444

Table B - 18: Logistic regression for Erica Browse – 0. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 18: Logistische Regression für Erika – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	-6.3232	0.9896	<.0001
WTRG	Water Regime	-0.5905	0.1451	<.0001
INTVAL	Interval Value	0.6228	0.1580	<.0001
SCD17,18	Soil Group 17 or 18	1.0381	0.1812	<.0001
GVD15	Erica Type	5.4871	0.8003	<.0001
GVD9	*Avenella* Type	2.9515	0.5728	<.0001
GVD5,6,16	Luxuriant Moss, Sparse Moss or Pasture Forest Types	1.2033	0.1684	<.0001
A_NOSH_T1	No Browse	-0.2397	0.0322	<.0001

Hosmer-Lemeshow statistic = 8.1603 with 8 DF (p=0.4180)
ROC = .79
A Priori Probability = .01, Threshold Probability = .06
n = 17615

Table B - 19: Logistic regression for Herb Browse – 1. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 19: Logistische Regression für Kräuter – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	6.1011	0.3698	<.0001
LN(A_KRSH_T1)	Herb Browse	1.5407	0.0848	<.0001
STD1_T2	Norway Spruce	-0.2286	0.0632	0.0003
INTVAL	Interval Value	-1.0617	0.0622	<.0001
GZD1,4	Growth Zone 1 or 4	-0.6325	0.0898	<.0001
GZD9,10,12,17	Growth Zone 9, 10, 12 or 17	0.7768	0.0743	<.0001
SCD4	Soil Group 4	-0.2956	0.0722	<.0001
GVD5,8	Luxuriant Moss or *Avenella* Types	-1.5180	0.1880	<.0001
GVD6,15	Sparse Moss or Erica Types	-0.9563	0.0802	<.0001
JUNGISH_T1, JUNGIISH_T1	Regen I or Regen II	-0.0472	0.00860	<.0001
QMD_T2	Quadratic Mean Diameter	0.0125	0.00239	<.0001

Hosmer-Lemeshow statistic =6.6203 with 8 DF (p=0.5781)
ROC = .79
A Priori Probability = .85, Threshold Probability = .70
n = 10976

Table B - 20: Logistic regression for Herb Browse – 0. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 20: Logistische Regression für Kräuter – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	-2.9432	0.3302	<.0001
INTVAL	Interval Value	0.4020	0.0593	<.0001
GZD1	Growth Zone 1	-0.4553	0.0879	<.0001
SCD14,17,18,19	Soil Group 14, 17, 18 or 19	0.7918	0.0872	<.0001
GVD1,2,19	Shade Herb, Moist Herb or Hydrophytic Shrub Types	0.3840	0.0916	<.0001
GVD5	Luxuriant Moss	-1.5092	0.1505	<.0001
GVD6	Sparse Moss	-0.7851	0.0679	<.0001
A_NOSH_T1	No Browse	-0.0713	0.00785	<.0001
C_BA^2	Change in Basal Area	0.000182	0.000063	0.0037
QMD_T2	Quadratic Mean Diameter	0.0103	0.00207	<.0001
RLD3	Concave Lower Slope	0.5151	0.1646	0.0017

Hosmer-Lemeshow statistic =13.7294 with 8 DF (p=0.0891)
ROC = .70
A Priori Probability = .24, Threshold Probability = .31
n = 7083

Table B - 21: Logistic regression for Fern Browse – 1. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 21: Logistische Regression für Farne – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	2.7210	0.5824	<.0001
SQRT(ELEV)	Elevation	0.5695	0.0730	<.0001
INTVAL	Interval Value	-1.1075	0.0839	<.0001
WTRG	Water Regime	0.1991	0.0936	0.0335
GZD1,4,8,12	Growth Zone 1, 4, 8 or 12	0.5690	0.1041	<.0001
GZD17	Growth Zone 17	-0.4672	0.1797	0.0093
ASD4,5,6	Southeast, South or Southwest Aspect	-0.4302	0.1048	<.0001
GVD4	Moderhumus in Conifer Stands	0.5658	0.0865	<.0001
GVD12	Competing Grass Cover	-0.5490	0.1770	0.0019
LN(A_FASH_T1)	Fern Browse	1.3563	0.1505	<.0001

Hosmer-Lemeshow statistic = 7.6517 with 8 DF (p=0.4682)
ROC = .73
A Priori Probability = .59, Threshold Probability = .56
n = 2845

Table B - 22: Logistic regression for Fern Browse – 0. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 22: Logistische Regression für Farne – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	-4.4876	0.2190	<.0001
A_NOSH_T1	No Browse	-0.0631	0.0107	<.0001
WTRG	Water Regime	0.3048	0.0678	<.0001
STD1_T2	Norway Spruce	0.3136	0.0733	<.0001
GZD8,11,12	Growth Zone 8, 11, or 12	0.5882	0.0882	<.0001
GZD18	Growth Zone 18	-0.5897	0.1648	0.0003
GZD20	Growth Zone 20	-1.2373	0.2847	<.0001
SCD4	Soil Group 4	0.3448	0.0786	<.0001
SCD14	Soil Group 14	0.9236	0.2069	<.0001
ASD1,2,8	North, Northeast or Northwest Aspect	0.6825	0.0705	<.0001
QMD_T2	Quadratic Mean Diameter	0.0114	0.00224	<.0001
GVD4,19	Moderhumus in Conifer Stands	0.8199	0.0734	<.0001

Hosmer-Lemeshow statistic = 9.4160 with 8 DF (p=0.3084)
ROC = .72
A Priori Probability = .06, Threshold Probability = .15
n = 15209

Table B - 23: Logistic regression for Grass Browse – 1. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 23: Logistische Regression für Gräser – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	4.7282	0.3316	<.0001
ELEV	Elevation	0.1119	0.00721	<.0001
INTVAL	Interval Value	-0.9861	0.0553	<.0001
GZD1	Growth Zone 1	0.3028	0.0905	0.0008
GZD2	Growth Zone 2	0.8745	0.2591	0.0007
GZD11	Growth Zone 11	-0.4556	0.0951	<.0001
SCD17	Soil Group 17	0.5483	0.1039	<.0001
GVD1,4,5,6,19	Shade Herb, Moderhumus, Luxuriant Moss, Sparse Moss or Hydrophytic Shrub Types	-0.6093	0.0694	<.0001
C_BA	Change in Basal Area	-0.00999	0.00262	0.0001
JUNGIISH_T1	Regen II	-0.0676	0.00711	<.0001
LN(A_GRSH_T1)	Grass Browse	1.8632	0.0793	<.0001
STANGSH_T2	Pole Stand	-0.0611	0.00902	<.0001
SCD3	Soil Group 3	-0.2259	0.0868	0.0093
GVD10	*Calluna* Type	-1.0539	0.4615	0.0224

Hosmer-Lemeshow statistic = 5.1275 with 8 DF (p=0.7439)
ROC = .80
A Priori Probability = .81, Threshold Probability = .66
n = 11022

Table B - 24: Logistic regression for Grass Browse – 0. Presented in the table are the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the Hosmer & Lemeshow test statistic and associated p-value, the area under the ROC curve, the a priori probability, the threshold probability, and the number of observations used to fit the model.

Tabelle B - 24: Logistische Regression für Gräser – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Null-Hypothese. Unter der Tabelle werden die Irrtumswahrscheinlichkeit des Hosmer & Lemeshow Tests, die Fläche unter der ROC-Kurve, die *a priori* Wahrscheinlichkeit, der Schwellenwert und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > ChiSq
INTERCEPT	Intercept	-3.1600	0.3586	<.0001
ELEV	Elevation	0.0832	0.00885	<.0001
INTVAL	Interval Value	0.3318	0.0621	<.0001
STD10_T2	Beech	-0.7384	0.1807	<.0001
STD0_T2	No Trees in Angle Count	0.3030	0.0999	0.0024
GZD1	Growth Zone 1	0.3723	0.0927	<.0001
GVD4	Moderhumus	-0.3130	0.0743	<.0001
GVD8,12	*Avenella* or Competing Grass Cover Types	1.5235	0.2425	<.0001
C_BA	Change in Basal Area	-0.0211	0.00291	<.0001
JUNGIISH_T1	Regen II	-0.0274	0.00995	0.0059
A_NOSH_T1	No Browse	-0.0575	0.00986	<.0001
STANGSH_T2	Pole Stand	-0.0575	0.0107	<.0001
GZD17	Growth Zone 17	-0.5325	0.1838	0.0038

Hosmer-Lemeshow statistic = 10.2307 with 8 DF (p=0.2492)
ROC = .67
A Priori Probability = .20, Threshold Probability = .27
n = 7037

12 APPENDIX C

Table C - 1: Logarithmic regression for REGEN I - 1 (with trees). The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 1: Logarithmische Regression für Verjüngung I „REGEN I" – 1 (mit Bäumen in WZP). Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	-0.04248	0.46690	0.9276
LN(JUNGISH_T1)	Regen I	0.45941	0.07540	<.0001
INTVAL	Interval Value	-0.20891	0.08043	0.0099
GZD7	Growth Zone 7	1.16372	0.29355	<.0001
GZD9	Growth Zone 9	0.32129	0.14655	0.0292
GZD10	Growth Zone 10	0.67253	0.12497	<.0001
GZD19,20	Growth Zone 19 or 20	-0.65695	0.16987	0.0001
ASD7	West Aspect	0.49085	0.11262	<.0001
SSD2_T2	2 Layer Stand	0.70219	0.09166	<.0001
GVD2	Moist Herb Type	0.93208	0.15445	<.0001
GVD19	Hydrophytic Shrub Type	-0.31313	0.14344	0.0299
A_GRSH_T1	Grass Browse	0.14977	0.02376	<.0001
LN(A_NOSH_T1)	No Browse	0.33003	0.06710	<.0001
C_QMD	Change in Quadratic Mean Diameter	0.01562	0.00594	0.0091

R^2=.54
n = 269

Table C - 2: Logarithmic regression for Regen II - 1 (with trees). The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 2: Logarithmische Regression für Verjüngung II „REGEN II" – 1 (mit Bäumen in WZP). Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	0.43426	0.08658	<.0001
LN(JUNGIISH_T1)	Regen II	0.77143	0.01591	<.0001
ELEV	Elevation	0.02012	0.00192	<.0001
INTVAL	Interval Value	-0.08074	0.01485	<.0001
STD1_T2	Norway Spruce	-0.34042	0.01684	<.0001
STD10_T2	Beech	0.17109	0.04521	0.0002
GZD6	Growth Zone 6	0.13581	0.04618	0.0033
GZD11,20	Growth Zone 11 or 20	0.07120	0.02258	0.0016
SSD1_T2	1 Layer Stand	-0.36713	0.01580	<.0001
LN(A_NDSH_T1)	Conifer Browse	0.30386	0.01291	<.0001
C_BA	Change in Basal Area	-0.00531	0.00090934	<.0001

R^2=.53
n = 4296

Table C - 3: Logarithmic regression for Regen II - 1 (no trees). The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 3: Logarithmische Regression für Verjüngung II „REGEN II" – 1 (ohne Bäume in WZP). Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	-0.19987	0.07572	0.0084
LN(JUNGIISH_T1)	Regen II	0.89566	0.03840	<.0001
LN(A_NDSH_T1), LN(A_LASH_T1)	Conifer or Deciduous Browse	0.39081	0.02330	<.0001
STD0_T2	No Trees in Angle Count	-0.05493	0.02354	0.0198
GZD3,7,19	Growth Zone 3, 7 or 19	-0.19286	0.05258	0.0003
SCD15,20,22	Soil Group 15, 20 or 22	-0.39417	0.07444	<.0001
SSD1_T2	1 Layer Stand	-0.47064	0.05011	<.0001
GVD2	Moist Herb Type	-0.13527	0.04872	0.0056
GVD4	Moderhumus in Conifer stand	-0.29029	0.04569	<.0001
GVD7	Moss Type	-0.45280	0.19315	0.0192
SSD1_T2 X ELEV	1 Layer Stand x Elevation	0.02939	0.00344	<.0001

R^2=.57
n = 1195

Table C - 4: Logarithmic regression for Regen II - 0 (with trees). The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 4: Logarithmische Regression für Verjüngung II „REGEN II" – 0 (mit Bäumen in WZP). Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	1.07297	0.02182	<.0001
LN(JUNGISH_T1)	Regen I	0.69388	0.00925	<.0001
ELEV	Elevation	-0.01625	0.00073075	<.0001
STD0_T2	No Trees in Angle Count	0.79406	0.02872	<.0001
GZD7,9,10	Growth Zone 7, 9 or 10	-0.05693	0.00631	<.0001
SCD3,4	Soil Group 3 or 4	0.03686	0.00632	<.0001
SCD22	Soil Group 22	0.15911	0.06167	0.0099
SSD1_T2	1 Layer Stand	-0.39395	0.01136	<.0001
GVD12	Competing Grass Cover	-0.03977	0.01208	0.0010
GVD17	Pioneer Vegetation Type	-0.46574	0.14417	0.0012
GVD19	Hydrophytic Shrub Type	0.11785	0.01655	<.0001
LN(A_NOSH_T1)	No Browse	-0.08797	0.00411	<.0001
[8]*OVERSH_T2*	Sum of Overstory Growth Classes	-0.03458	0.00162	<.0001

R^2=.77
n = 6266

[8] OVERSH_T2 = STANGSH_T2 + BHISH_T2 + BHIISH_T2 + STARKSH_T2

Table C - 5: Logarithmic regression for Regen II – Larch. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 5: Logarithmische Regression für Verjüngung II „REGEN II" – Lärche. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	-0.44363	0.00701	<.0001
LA_JUNGIISH_T1	Larch Regen II	0.20775	0.00192	<.0001
LA_JUNGISH_T1	Larch Regen I	0.22942	0.00487	<.0001
ELEV	Elevation	0.00190	0.00055896	0.0007
STD1_T2	Norway Spruce	-0.01117	0.00455	0.0142
STD3 _T2	White Fir	0.17559	0.01468	<.0001
STD6_T2	Stone Pine	-0.19169	0.05067	0.0002
SCD1	Soil Group 1	-0.08940	0.02170	<.0001
SCD5	Soil Group 5	0.03043	0.01258	0.0156
GVD14	Subalpine Dwarf Shrub Type	0.27652	0.03067	<.0001
GVD16	Pasture Forest Type	0.05388	0.01224	<.0001

R^2=.71
n = 8945

Table C - 6: Logarithmic regression for Regen II – Broadleaved Species. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 6: Logarithmische Regression für Verjüngung II „REGEN II" – Laubbäume. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	0.20386	0.01590	<.0001
LN(BL_JUNGIISH_T1)	Broadleaved Regen II	0.79131	0.00711	<.0001
LN(BL_JUNGISH_T1)	Broadleaved Regen I	0.83675	0.03194	<.0001
ELEV	Elevation	-0.01378	0.00137	<.0001
STD10_T2,STD11_T2	Beech or Oak	0.32726	0.02815	<.0001
STD41_T2	Mixed Deciduous	0.16255	0.01750	<.0001
STD40_T2	Mixed Coniferous	0.02940	0.01199	0.0142
GZD3	Growth Zone 3	0.22901	0.05166	<.0001
GZD6	Growth Zone 6	0.11713	0.02959	<.0001
GZD10,19	Growth Zone 10 or 19	0.08310	0.01641	<.0001
SCD6	Soil Group 6	-0.09803	0.03873	0.0114
GVD1	Shade Herb Type	0.11067	0.01724	<.0001
GVD6,12	Sparse Moss or Competing Grass Cover Types	-0.04693	0.01098	<.0001
GVD13	Depletion or Litter Erosion Types	0.42218	0.12736	0.0009

R^2=.68
n = 8945

Table C - 7: Logarithmic regression for No Browse – 1. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 7: Logarithmische Regression für Keine Äsung – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	1.31537	0.05834	<.0001
LN(A_NOSH_T1)	No Browse	1.12263	0.00984	<.0001
LN(JUNGIISH_T1)	Regen II	0.18612	0.00744	<.0001
INTVAL	Interval Value	-0.38183	0.00941	<.0001
STD0_T2	No Trees in Angle Count	-0.46306	0.02462	<.0001
STD1_T2	Norway Spruce	0.05427	0.01000	<.0001
STD10_T2	Beech	0.14062	0.02325	<.0001
SCD5	Soil Group 5	-0.07185	0.02747	0.0089
GVD1,4	Shade Herb or Moderhumus	0.05828	0.01201	<.0001
GVD6,7	Sparse Moss or Moss Types	0.11140	0.01313	<.0001
QMD_T2	Quadratic Mean Diameter	-0.00666	0.00044619	<.0001
C_BA	Change in Basal Area	0.00676	0.00043417	<.0001
[9]*OVERSH_T2*	Sum of Overstory Growth Classes	0.03460	0.00214	<.0001

R^2=.69
n = 9352

[9] OVERSH_T2 = STANGSH_T2 + BHISH_T2 + BHIISH_T2 + STARKSH_T2

Table C - 8: Logarithmic regression for No Browse – 0. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 8: Logarithmische Regression für Keine Äsung – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	-1.25813	0.08660	<.0001
$JUNGIISH\_T1^2$	Regen II	0.00500	0.00017934	<.0001
$ELEV^2$	Elevation	-0.00135	0.00009560	<.0001
INTVAL	Interval Value	0.21610	0.01507	<.0001
STD1_T2	Norway Spruce	0.23583	0.01740	<.0001
GZD9	Growth Zone 9	-0.20297	0.02575	<.0001
GZD15	Growth Zone 15	0.16418	0.02511	<.0001
GZD18,20	Growth Zone 18 or 20	0.24728	0.02707	<.0001
SCD3,10	Soil Group 3 or 10	0.16927	0.02293	<.0001
GVD1,2,4,6	Shade Herb, Moist Herb, Moderhumus or Sparse Moss Types	0.35621	0.01733	<.0001
A_GRSH_T1	Grass Browse	-0.01577	0.00327	<.0001
[10] $ASUNGSH\_T1^2$	Sum of Browse Classes	0.01059	0.00045200	<.0001
C_BA	Change in Basal Area	0.01279	0.00089259	<.0001
[11] $OVERSH\_T2^2$	Sum of Overstory Growth Classes	0.00380	0.00019050	<.0001

R^2=.63
n = 3506

[10] ASUNGSH_T1 = A_NDSH_T1 + A_LASH_T1 + A_STSH_T1
[11] OVERSH_T2 = STANGSH_T2 + BHISH_T2 + BHIISH_T2

Table C - 9: Logarithmic regression for Deciduous Browse – 1. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 9: Logarithmische Regression für Laubbäume – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	0.97656	0.10894	<.0001
LN(A_LASH_T1)	Deciduous Browse	0.95326	0.02512	<.0001
ELEV	Elevation	-0.03065	0.00341	<.0001
INTVAL	Interval Value	-0.15666	0.01774	<.0001
STD1_T2	Norway Spruce	-0.08919	0.02432	0.0003
GZD6	Growth Zone 6	0.10929	0.03892	0.0050
GZD9,10,14	Growth Zone 9, 10 or 14	0.30488	0.02350	<.0001
SCD2	Soil Group 2	0.08846	0.02949	0.0027
SCD4	Soil Group 4	-0.08364	0.03415	0.0144
SCD11	Soil Group 11	0.30241	0.03390	<.0001
A_NOSH_T1	No Browse	-0.06109	0.00396	<.0001
C_BA	Change in Basal Area	-0.00887	0.00089479	<.0001
JUNGIISH_T1^2	Regen II	-0.00130	0.00020882	<.0001
[12]*OVERSH_T2*	Sum of Overstory Growth Classes	-0.01125	0.00276	<.0001

R^2=.65
n = 1929

[12] OVERSH_T2 = STANGSH_T2 + BHISH_T2

Table C - 10: Logarithmic regression for Deciduous Browse – 0. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 10: Logarithmische Regression für Laubbäume – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	-0.29118	0.02683	<.0001
A_NOSH_TI	No Browse	-0.02289	0.00077921	<.0001
ELEV	Elevation	-0.03384	0.00075900	<.0001
INTVAL	Interval Value	0.15828	0.00471	<.0001
STD1_T2	Norway Spruce	-0.07993	0.00492	<.0001
STD10_T2, STD41_T2	Beech or Mixed Deciduous	0.31859	0.01069	<.0001
GZD1,4	Growth Zone 1 or 4	-0.10270	0.00797	<.0001
GZD6,7,8	Growth Zone 6, 7 or 8	0.14791	0.01241	<.0001
GZD9	Growth Zone 9	-0.04023	0.00906	<.0001
GZD10	Growth Zone 10	0.06966	0.00916	<.0001
GZD13	Growth Zone 13	0.02216	0.00675	0.0010
GVD1,19	Shade Herb or Hydrophytic Shrub Types	0.26700	0.00853	<.0001
GVD2,4	Moist Herb or Moderhumus in Conifer Stands	0.06180	0.00561	<.0001
GVD3	Thermophilic Herb Type	0.39415	0.03760	<.0001
C_BA	Change in Basal Area	-0.00303	0.00021822	<.0001

R^2=.50
n = 10203

Table C - 11: Logarithmic regression for Shrub Browse – 1. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 11: Logarithmische Regression für Sträucher – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	1.12884	0.13440	<.0001
LN(A_STSH_T1)	Shrub Browse	1.02878	0.03023	<.0001
ELEV	Elevation	-0.03309	0.00410	<.0001
INTVAL	Interval Value	-0.19062	0.02158	<.0001
GZD20	Growth Zone 20	-0.26444	0.04659	<.0001
SCD4	Soil Group 4	-0.24565	0.03645	<.0001
SCD8	Soil Group 8	0.19524	0.04988	<.0001
SCD9,13	Soil Group 9 or 13	-0.12076	0.03774	0.0014
GVD4,19	Moderhumus in Conifer Stands or Hydrophytic Shrub Types	-0.19228	0.02230	<.0001
A_NOSH_T1	No Browse	-0.02888	0.00484	<.0001
JUNGIISH_T1	Regen II	-0.03137	0.00294	<.0001

R^2=.67
n = 1216

Table C - 12: Logarithmic regression for Shrub Browse – 0. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 12: Logarithmische Regression für Sträucher – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	0.03446	0.02033	0.0901
ELEV	Elevation	-0.02697	0.00056818	<.0001
A_NOSH_T1	No Browse	-0.02104	0.00060818	<.0001
INTVAL	Interval Value	0.07734	0.00354	<.0001
STD5,11	Black Pine	0.26079	0.02370	<.0001
STD10	Beech	-0.15841	0.00864	<.0001
GZD2	Growth Zone 2	0.27944	0.03101	<.0001
GZD3	Growth Zone 3	0.14968	0.02667	<.0001
GZD8,9,10	Growth Zone 8, 9 or 10	-0.04635	0.00455	<.0001
SCD10	Soil Group 10	0.09058	0.02587	0.0005
SCD21	Soil Group 21	0.22544	0.03218	<.0001
ASD4,6	Southeast or Southwest Aspect	0.05184	0.00475	<.0001
SSD1_T2	1 Layer Stands	-0.02713	0.00419	<.0001
GVD1,19	Shade Herb or Hydrophytic Shrub Types	0.23994	0.00656	<.0001
GVD3,14	Thermophilic Herb or Subalpine Dwarf Shrub Types	0.15478	0.01889	<.0001
GVD6,7	Sparse Moss or Moss Types	-0.06930	0.00405	<.0001
GVD20	Floodplain Type	0.67731	0.05969	<.0001
C_BA	Change in Basal Area	-0.00138	0.00016916	<.0001
[13]*GRP_GZ*	Group of Growth Zones	0.01145	0.00070127	<.0001

R^2=.38
n = 11127

[13] GRP_GZ = GZD13 OR GZD14 OR GZD15 OR GZD18

Table C - 13: Logarithmic regression for Raspberry Browse – 1. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 13: Logarithmische Regression für Himbeere – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	1.17517	0.14944	<.0001
LN(A_HISH_T1)	Raspberry Browse	0.87858	0.03255	<.0001
ELEV	Elevation	-0.03088	0.00416	<.0001
INTVAL	Interval Value	-0.22450	0.02406	<.0001
STD1_T2	Norway Spruce	-0.10280	0.02729	0.0002
STD4_T2	Scots Pine	0.28576	0.06649	<.0001
GZD1,4	Growth Zone 1 or 4	0.10080	0.02939	0.0006
SCD14,17,18	Soil Group 14, 17 or 18	-0.16499	0.04245	0.0001
SCD22	Soil Group 22	-0.42867	0.10215	<.0001
GVD4,19	Moderhumus or Hydrophytic Shrub Types	0.39081	0.02938	<.0001
A_NOSH_T1	No Browse	-0.03775	0.00649	<.0001
JUNGIISH_T1	Regen II	-0.03869	0.00299	<.0001

R^2=.69
n = 1220

Table C - 14: Logarithmic regression for Raspberry Browse - 0 . Tbe table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R2 and the number of observations used to fit the model.

Tabelle C - 14: Logarithmische Regression für Himbeere – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	-0.08873	0.02136	<.0001
A_NOSH_T1	No Browse	-0.01139	0.00060897	<.0001
ELEV	Elevation	-0.01319	0.00055240	<.0001
INTVAL	Interval Value	0.07240	0.00351	<.0001
STD0_T2	No Trees in Angle Count	0.14383	0.00744	<.0001
GZD1,19	Growth Zone 1 or 19	0.03419	0.00660	<.0001
GZD2,3,4,7,21	Growth Zone 2, 3, 4, 7, 21	0.11434	0.00891	<.0001
SCD6	Soil Group 6	-0.05651	0.01308	<.0001
SCD21	Soil Group 21	-0.21422	0.01924	<.0001
SCD17,18,19,20	Soil Group 17, 18, 19, 20	-0.09948	0.00414	<.0001
SCD9,11,13	Soil Group 9, 11, 13	0.06139	0.00833	<.0001
GVD19	Hydrophytic Shrub	0.79334	0.01379	<.0001
GVD1,4,20	Shade Herb, Moderhumus or Floodplain Types	0.09621	0.00398	<.0001
JUNGIISH_T1	Regen II	-0.00712	0.00069284	<.0001
[14]*OVERSH_T2*	Sum of Overstory Growth Classes	-0.00744	0.00074670	<.0001
C_BA	Change in Basal Area	-0.00437	0.00020200	<.0001

R^2=.41
n = 12033

[14] OVERSH_T2 = STANGSH_T2 + BHISH_T2 + BHIISH_T2 + STARKSH_T2

Table C - 15: Logarithmic regression for Blueberry Browse – 1. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 15: Logarithmische Regression für Heidelbeere – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	0.18189	0.07259	0.0123
LN(A_HESH_T1)	Blueberry Browse	1.17272	0.01427	<.0001
ELEV	Elevation	0.02920	0.00165	<.0001
SLPE	Slope	-0.02342	0.00300	<.0001
INTVAL	Interval Value	-0.14534	0.01209	<.0001
C_BA	Change in Basal Area	0.00312	0.00061973	<.0001
STANGSH_T2	Pole Stand	-0.00986	0.00251	<.0001
STD0_T2	No Trees in Angle Count	-0.13414	0.02153	<.0001
STD1_T2	Norway Spruce	-0.04490	0.01311	0.0006
GZD17	Growth Zone 17	-0.11224	0.03136	0.0003
SCD2	Soil Group 2	-0.08853	0.02494	0.0004
SCD6	Soil Group 6	0.11101	0.03314	0.0008
GVD1,2,12,18	Shade Herb, Moist Herb, Competing Grass Cover or Seep Vegetation Types	-0.28435	0.06896	<.0001
GVD4	Moderhumus in Conifer Stands	-0.34816	0.02316	<.0001
GVD19	Hydrophytic Shrub Type	-0.47816	0.05294	<.0001

R^2=.74
n = 3812

Table C - 16: Logarithmic regression for Blueberry Browse – 0. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 16: Logarithmische Regression für Heidelbeere – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	-0.42619	0.02215	<.0001
ELEV	Elevation	0.02928	0.00073594	<.0001
SLPE	Slope	-0.02202	0.00086895	<.0001
$JUNGISH\_T1^2$	Regen I	-0.00067503	0.00007529	<.0001
INTVAL	Interval Value	0.06167	0.00388	<.0001
GVD6,14	Sparse Moss or Subalpine Dwarf Shrub Types	0.70433	0.01326	<.0001
SCD2	Soil Group 2	0.14737	0.00521	<.0001
STD41_T2	Mixed Deciduous	-0.01671	0.00510	0.0011
ASD2,8	Northeast or Northwest Aspect	0.06189	0.00489	<.0001
GVD4	Moderhumus	-0.02668	0.00450	<.0001
STD0_T2	No Trees in Angle Count	0.03038	0.00624	<.0001

R^2=.44
n = 9166

Table C - 17: Logarithmic regression for Erica Browse – 1. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 17: Logarithmische Regression für Erika – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	3.07178	0.23845	<.0001
A_ERSH_T1	Erica Browse	0.10926	0.01263	<.0001
WTRG	Water Regime	-0.28099	0.03708	<.0001
INTVAL	Interval Value	-0.39848	0.04088	<.0001
GZD1	Growth Zone 1	-0.35946	0.10343	0.0006
GZD14,17	Growth Zone 14 or 17	0.20267	0.05135	<.0001
GZD20	Growth Zone 20	-0.65060	0.16602	0.0001
GVD10	*Calluna* Type	0.30275	0.08625	0.0005
GVD15	Erica Type	0.59298	0.05520	<.0001
A_NOSH_T1	No Browse	-0.04688	0.01333	0.0005
JUNGIISH_T1	Regen II	-0.01452	0.00672	0.0314

R^2=.80
n = 318

Table C - 18: Logarithmic regression for Herb Browse – 1. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 18: Logarithmische Regression für Kräuter – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	0.99962	0.05663	<.0001
LN(A_KRSH_T1)	Herb Browse	0.84888	0.01090	<.0001
WTRG	Water Regime	0.05132	0.00800	<.0001
INTVAL	Interval Value	-0.21475	0.00926	<.0001
STD40_T2	Mixed Coniferous	0.04778	0.01086	<.0001
STD41_T2	Mixed Deciduous	0.10296	0.01330	<.0001
GZD1,4	Growth Zone 1 or 4	-0.26931	0.01925	<.0001
GZD9,10,17	Growth Zone 9, 10 or 17	0.16931	0.01030	<.0001
GZD12	Growth Zone 12	0.11405	0.02295	<.0001
SCD4	Soil Group 4	-0.18160	0.01489	<.0001
GVD5,6,8,15	Luxuriant Moss, Sparse Moss, *Avenella* type or Erica Type	-0.41888	0.01838	<.0001
QMD_T2	Quadratic Mean Diameter	0.00337	0.00032566	<.0001
JUNGISH_T1, JUNGIISH_T1	Regen I, Regen II	-0.01617	0.00141	<.0001

R^2=.61
n = 7767

Table C - 19: Logarithmic regression for Herb Browse – 0. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 19: Logarithmische Regression für Kräuter – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	-0.36231	0.04791	<.0001
A_NOSH_T1	No Browse	-0.02769	0.00126	<.0001
QMD_T2	Quadratic Mean Diameter	0.00368	0.00032639	<.0001
C_BA	Change in Basal Area	-0.00249	0.00041220	<.0001
STD41_T2	Mixed Deciduous	0.07403	0.01944	0.0001
INTVAL	Interval Value	0.16726	0.00863	<.0001
GZD1	Growth Zone 1	-0.12820	0.01069	<.0001
GVD6	Sparse Moss Type	-0.41282	0.01028	<.0001
GVD5	Luxuriant Moss Type	-0.54448	0.01676	<.0001
GVD2	Moist Herb Type	0.14096	0.03386	<.0001
GVD1,16,18,19	Shade Herb, Pasture Forest, Seep Vegetation and Hydrophytic Shrub Types	0.39017	0.02054	<.0001
SCD14	Soil Group 14	0.27900	0.05075	<.0001
SCD3	Soil Group 3	0.06178	0.01744	0.0004
SCD17,18,19,21,22	Soil Group 17, 18, 19, 21 or 22	0.44555	0.01851	<.0001

R^2=.58
n = 4674

Table C - 20: Logarithmic regression for Fern Browse – 1. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 20: Logarithmische Regression für Farne – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	1.57391	0.09862	<.0001
LN(A_FASH_T1)	Fern Browse	0.97814	0.02227	<.0001
ELEV	Elevation	0.03176	0.00212	<.0001
WTRG	Water Regime	0.06333	0.01577	<.0001
INTVAL	Interval Value	-0.46153	0.01407	<.0001
GZD1,8	Growth Zone 1 or 8	0.20629	0.02200	<.0001
GZD4,12	Growth Zone 4 or 12	0.17028	0.02274	<.0001
GZD17	Growth Zone 17	-0.18428	0.03221	<.0001
SCD18	Soil Group 18	-0.07866	0.02745	0.0042
ASD4,5,6	Southeast, South, Southwest Aspect	-0.17847	0.01818	<.0001
GVD4	Moderhumus in Conifer Stands	0.19063	0.01484	<.0001
GVD12	Competing Grass Cover	-0.20948	0.03083	<.0001
QMD_T2	Quadratic Mean Diameter	0.00131	0.00046286	0.0049
STARKSH_T2	Old Growth Stand	0.01044	0.00478	0.0292

R^2=.70
n = 1899

Table C - 21: Logarithmic regression for Fern Browse – 0. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 21: Logarithmische Regression für Farne – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	-0.11226	0.00591	<.0001
WTRG²	Water Regime	0.00700	0.00053497	<.0001
A_NOSH_T1²	No Browse	-0.00068677	0.00004381	<.0001
STD1_T2	Norway Spruce	0.05572	0.00381	<.0001
GZD1,3	Growth Zone 1 or 3	-0.01708	0.00511	0.0008
GZD8,12	Growth Zone 8 or 12	0.23303	0.01138	<.0001
GZD11	Growth Zone 11	0.19476	0.00998	<.0001
GZD18,20	Growth Zone 18 or 20	-0.07152	0.00440	<.0001
SCD4	Soil Group 4	0.06868	0.00443	<.0001
SCD14	Soil Group 14	0.50587	0.02381	<.0001
ASD1,2,8	North, Northeast or Northwest Aspect	0.14689	0.00400	<.0001
GVD4	Moderhumus in Conifer Stands	0.19168	0.00552	<.0001
GVD19	Hydrophytic Shrub Type	0.23263	0.00853	<.0001
GVD2	Moist Herb Type	0.01733	0.00549	0.0016
QMD_T2	Quadratic Mean Diameter	0.00201	0.00012290	<.0001

R^2=.37
n = 9982

Table C - 22: Logarithmic regression for Grass Browse – 1. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 22: Logarithmische Regression für Gräser – 1. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	0.58528	0.05374	<.0001
LN(A_GRSH_T1)	Grass Browse	1.00535	0.01152	<.0001
ELEV	Elevation	0.03223	0.00118	<.0001
INTVAL	Interval Value	-0.20534	0.00907	<.0001
GZD1	Growth Zone 1	0.11445	0.01775	<.0001
GZD11,16	Growth Zone 11 or 16	-0.17516	0.01682	<.0001
GZD18,20	Growth Zone 18 or 20	-0.09194	0.01662	<.0001
SCD3	Soil Group 3	-0.07597	0.01588	<.0001
SCD17	Soil Group 17	0.11799	0.01336	<.0001
GVD2,16	Moist Herb or Pasture Forest Types	0.19244	0.01404	<.0001
GVD3,8,11,12,15,18	Thermophilic Herb, *Avenella* Type, *Sphagnum-Vaccinium-Avenella Type*, Competing Grass Cover, Erica or Seep Vegetation Types	0.22263	0.01250	<.0001
GVD13,20	Depletion or Litter Erosion sites or Floodplain Types	0.40132	0.06190	<.0001
C_BA	Change in Basal Area	-0.00592	0.00045481	<.0001
JUNGIISH_T1	Regen II	-0.01731	0.00127	<.0001
STANGSH_T2	Pole Stand	-0.01834	0.00175	<.0001

R^2=.70
n = 7767

Table C- 23: Logarithmic regression for Grass Browse – 0. The table presents the model parameters, their description, estimated coefficient, standard error and p-value. Below the table is the R^2 and the number of observations used to fit the model.

Tabelle C - 23: Logarithmische Regression für Gräser – 0. Die Tabelle enthält die Parameter, ihre Beschreibung, die geschätzten Koeffizienten, den Standardfehler und die Wahrscheinlichkeit für das Zutreffen der Nullhypothese. Unter der Tabelle wird das Bestimmtheitsmaß und die Anzahl der Beobachtungen angegeben.

Parameter	Parameter Description	Parameter Estimate	Standard Error	Pr > |t|
INTERCEPT	Intercept	-0.46701	0.05267	<.0001
ELEV	Elevation	0.04443	0.00145	<.0001
SQRT(A_NOSH_T1)	No Browse	-0.15094	0.00691	<.0001
INTVAL	Interval Value	0.17079	0.00906	<.0001
STD0_T2, STD3_T2	No Trees in Angle Count or Larch	0.27363	0.01780	<.0001
STD1_T2	Norway Spruce	0.03096	0.01066	0.0037
STD10_T2	Beech	-0.22577	0.01830	<.0001
GZD1	Growth Zone 1	0.20637	0.01425	<.0001
GZD17	Growth Zone 17	-0.24322	0.02097	<.0001
GVD4	Moderhumus in Conifer Stands	-0.15828	0.01014	<.0001
GVD8,12,16	Avenella Type, Competing Grass Cover or Pasture Forest Types	0.72471	0.04325	<.0001
GVD18	Seep Vegetation Type	0.27411	0.06377	<.0001
C_BA	Change in Basal Area	-0.00863	0.00041293	<.0001
LN(JUNGIISH_T1)	Regen II	-0.05333	0.00532	<.0001
LN(STANGSH_T2)	Pole Stand	-0.08823	0.00513	<.0001

R^2=.53
n = 4369